RETURNS TO VOCATIONAL EDUCATION AND TRAINING: RETENTION, MOBILITY, AND WAGES

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CHAPTER 1

Introduction

Education is generally seen as one of the most important investments in a person's life. Education raises earnings, improves health, adds to a person's positive habits, and improves overall life satisfaction (Becker 1993). The benefits of education are not restricted to the individual, but spill over to firms and the economy as a whole (Blundell et al. 1999). A more educated workforce improves a firm's productivity and profitability and thus enhances national economic growth.

Human capital theory, as pioneered by Schultz (1961) and Becker (1962), views the decision to invest in education as analogous to investments in tangible forms of capital. However, while investments in physical capital are strictly the firm's own decision, investments in human capital involve interactions between firms and their workers. Firms invest in their workers' human capital to improve efficiency and increase overall firm output, at the cost of the foregone value of the workers' time not spent on productive activities. Workers invest in human capital to improve their labor market opportunities and to maximize earnings, at the cost of the foregone value of time spent in education and training.

Despite the wealth of literature on human capital investments, some fundamental empirical questions remain unsolved. In particular, researchers have paid little attention to the question of how changing market environments might affect returns on investment. To sustain their profitability and employability, both firms and individuals might need to adapt their investment strategies to respond to market changes. Only few studies investigate the role of changing market environments in determining returns to educational investment. Yet, this type of evidence is crucial for choosing an optimal investment strategy both for the firm and the individual. This doctoral thesis aims at providing an elaborate analysis of the factors influencing the realized returns to educational investments.

Throughout the analyses, I focus on dual vocational education and training (VET), as in this type of education both firms and individuals are involved in the investment decision (Muehlemann et al. 2007). VET combines formal education at vocational schools with on-the-job training at a training firm. My empirical analyses are based on data from Germany and Switzerland, two countries with a strong VET tradition. Unlike other sectors of the educational system, VET is market-driven, i.e., individuals have no guarantee of receiving a training place, nor are firms obligated to provide training.

The first project of this doctoral thesis analyzes how firms that provide and pay for training secure their return on human capital investment. For these firms, the outcome of interest is a better-educated and thus more productive workforce. To realize this outcome, firms must be able to retain at least some of their trained workers. The new training literature highlights the importance of labor market frictions for a firm's ability to retain their training graduates. In this project, I investigate how firms retain their graduates if they are embedded in markets without these favorable market frictions.

The second project analyzes individual investment decisions and focuses on the skill set that individuals acquire during their education. For individuals, the outcomes of interest are employability and earnings. To realize these outcomes, individuals must acquire skill sets that are valued on the labor market. I investigate the value of different types of skill sets and how these skill sets determine individuals' labor market outcomes.

The third project combines the firm and the individual perspectives and analyzes educational outcomes in a dynamic setting. Of course, firms and individuals want to maximize both their short-term and their long-term returns on investment. In the long run, market dynamics might fundamentally alter the working environment and might lead firms to demand different types of skills. Workers, in turn, have to respond to changed skill demands. In this project, I investigate how skill requirements have changed over time and how these changes are related to changes in wages.

The existence of firm-financed training is not easily explained by standard human capital theory. According to this theory, profit-maximizing firms should be unwilling to offer and pay for the general training of workers who are likely to leave the firm after training. Instead, firms would simply free-ride on the investment of other firms by hiring fully trained workers. Starting with Harhoff and Kane (1997), researchers have investigated this apparent paradox, and most explanations focus on some type of market imperfection that allows training firms to recoup the training costs by extracting rents from graduates who stay with them at the end of the training period (Acemoglu and Pischke 1998, 1999a, 1999b; Katz and Ziderman 1999; Booth and Bryan 2007; Mohrenweiser and Backes-Gellner 2010). Indeed, researchers argue that the absence of strict labor market regulations explains a firm's reluctance to invest in the general skills of their apprentices (Acemoglu and Pischke 1999b; Bassanini and Brunello 2008).

Thus far, little discussion exists on whether and, if so, how a large-scale VET system might function well in a different market environment. In this regard the Swiss case is highly insightful. Although the Swiss labor market is weakly regulated by international standards, it has a highly successful VET system (Muehlemann and Wolter 2011; Ryan, Backes-Gellner, Teuber, and Wagner 2013). To explain why firms invest in training if they are embedded in weakly regulated labor markets, I argue that firms use pay-for-performance plans to incentivize their graduates to stay. Personnel economic theory predicts that the most productive workers self-select into performance-pay jobs because of higher expected returns (Lazear 1986, 2000). I empirically test whether this prediction also applies to graduates from vocational education and training programs.

My analysis uses representative data from a large employer-employee panel, which contains unique data on the base and bonus payments of individual employees. With this information, I construct two performance pay measures, one reflecting the amount of performance pay in relation to the total pay in a firm and the other the performance pay coverage, the share of workers receiving performance pay.

To account for unobserved time-invariant firm heterogeneity and potential endogeneity, I run instrumental variable regressions. I instrument the performance pay measures with a variable on the occupational position, which provides information on the hierarchical position of employees. The idea of this IV strategy is that the occupational position should be positively correlated both with the amount of performance pay and the likelihood of receiving it. The higher the occupational position, the higher the amount of performance pay, and the higher the likelihood of receiving it. However, given that young training graduates all start in the same occupational position, this variable should not have any effect on the retention of training graduates.

The empirical analysis shows that the occupational position is indeed a valid and strong instrument for the performance pay measures. I find that both the amount of performance pay and the likelihood of receiving it have a highly significant positive effect on the retention of training graduates. Given their higher retention success, performance-pay firms thus should also be more inclined to invest in general training than firms with fixed salaries. Market frictions might thus not be a necessary prerequisite for firms to offer general training. Instead, even in competitive markets firms can offer and pay for general training if they adjust their payment strategy to incentivize their graduates to stay. Pay-for-performance plans are a successful means for training firms to secure their returns on educational investments.

Even if firms offer and pay for training, individuals must take the offer and be willing to participate in training. This will only be the case if they benefit from their training effort. In the second project, I shift the focus to the individual perspective and investigate how training graduates secure their returns to educational investment. For the analysis, I draw on recent literature that suggests that the Mincer earnings equation—using the number of years of formal education as a measure of skill—cannot account for the considerable heterogeneity that exists within the same education group (Ingram and Neumann 2006; Poletaev and Robinson 2008; Kambourov and Manovskii 2009a, 2009b). This literature argues that different colleges and training institutions deliver different types of skill sets to their students, and therefore graduates achieve uneven levels of preparedness upon graduation.

Lazear's (2009) skill-weights approach formalizes this idea in a tractable and testable model. He assumes that all skills are general in their nature, but that the combination of single skills varies across firms. Because firms demand different combinations and different weights of skills, skill combinations become firm-specific. Lazear thus introduces a new concept of human capital specificity. The advantage of his view of human capital is that it provides a more differentiated explanation for employability and earnings opportunities.

I transfer Lazear's idea to the case of VET occupations and characterize these occupations in terms of their skill bundles. While Lazear defines human capital specificity on the firm level, I thus define it on the occupational level, assuming that skill weights are constant on the occupational level. I compare the skill bundles of VET occupations with the market weight to determine the degree of specificity of occupational skill bundles. The market weight comprises the market demand for different skill bundles. If the market demand is high, i.e., many occupations use a certain skill bundle, then the degree of specificity of that skill bundle is low and vice versa. This approach allows me to define and rank VET occupations in terms of their degree of specificity.

I then investigate the effect of occupational specificity on individual employment opportunities and earnings. In addition, I compare VET occupations with each other to determine how similar they are in terms of their skill bundles and how the skill similarity between the original occupation and the new occupation affects changes in wages. Instead of leaving the training firm voluntarily for another firm that offers better opportunities, training graduates might of course be laid off by their firm. The analysis of how well VET prepares workers for coping with layoffs is particularly valuable, because it provides information on the riskiness of a worker's educational investment. Therefore, I decide to focus my analysis on laid-off individuals and investigate whether occupational specificity determines how quickly individuals find reemployment, what type of reemployment they find, and how occupational specificity affects wages.

My empirical analyses show that individuals trained in more specific occupations are less likely to find reemployment in a different occupation and are more likely to suffer prolonged periods of unemployment than individuals trained in more general occupations. In addition, I find that occupational specificity has a significantly positive effect on wages. Individuals trained in more specific occupations receive a wage premium compared to individuals trained in more general occupations. Finally, I show that workers, who move to new occupations that are similar to their old occupation in terms of the underlying skill bundles, suffer smaller wage losses than workers who move between more occupations that are more dissimilar. This finding provides evidence that skills are indeed transferable across occupations.

My second contribution in this doctoral thesis is to show that occupational specificity crucially determines workers' labor market success. I show that a trade-off exists between more specific skill bundles that pay higher wages and more general skill bundles that increase worker's mobility. Because more specific skill bundles hamper individuals' mobility, firms might have a stronger interest in providing training in these skill bundles. Because more specific skill bundles provide individuals with fewer outside options, they are more likely to stay with their training firm. However, more specific skill bundles also imply that individuals are less adaptable to changing skill demands. In the long run, therefore, firms are probably better advised to provide training in more general skill bundles to build up a workforce that is able to cope with technological change.

In the third project, I explicitly focus on long-term returns to educational investments and investigate how labor market dynamics affect these returns. Structural change and technological shifts are related to an organizational restructuring that affects the overall demand for certain skills, ultimately changing the market value of the individual's human capital. That technological change fundamentally alters the skill requirements has long been recognized (Katz and Murphy 1992; Card and DiNardo 2002; Autor, Levy, and Murnane 2003; Autor, Katz, and Kearny 2006, 2008; Lemieux 2006a; Goos and Manning 2007; Goos, Manning, and Salomons 2009, 2014; Altonji, Kahn, and Speer 2014).

Previous research finds that technological change is associated with a polarization of wages, where moderately skilled workers experience a decline in relative wages, while low-skilled and high-skilled workers experience an increase. The common explanation for this development is that middle-skilled workers perform mostly routine tasks that are easily substitutable by computers. However, research in this field suffers two major shortcomings. First, since most of these studies are investigating the United States and the United Kingdom, their results are not easily transferable to countries with fundamentally different educational systems. While middle-skilled workers have a high-school degree or some college in the Anglo-Saxon countries, in countries such as Germany and Switzerland, middle-skilled workers have a VET degree (Autor 2013).

These countries have institutionalized processes of regularly updating VET curricula to include latest technological developments and highly innovative firms participate in this updating process. In addition, most training firms lay particular emphasis on further training their incumbent workers. Because of these measures, middle-skilled workers in Germany and Switzerland are potentially less affected by technological change than middle-skilled workers in Anglo-Saxon countries. Second, most previous studies in the field use information on skill requirements that are measured at only one point in time. However, the theoretical argument emphasizes that the introduction of new technologies fundamentally changes skill requirements. To adequately measure these effects, empirical analyses ought to use panel data on skill requirements to track changes in skill requirements in different occupations.

In the third project, I address both of these shortcomings. Again, I draw on Lazear's skill weights approach and characterize occupations by skill bundles. In the empirical analysis, I combine German administrative records from 1975 through 2008 with detailed data on occupational skills from different waves of the BIBB/IAB Employment Surveys. These surveys allow me to identify how skill bundles in occupations changed over time. I distinguish between cognitive, interactive, and manual skills and investigate how the share of these skills changes within occupations and relate these changes to changes in the wage structure.

In the descriptive analysis, I show that skill bundles underwent substantial changes. Over all occupations, the share of cognitive skills increased, while the share of manual skills decreased. This finding suggests that any longitudinal analysis relating skills to wages might be potentially biased if it does not account for the fact that skill requirements change over time.

I also show that Germany experienced an increase in top-end wage inequality from the late 1970s through the mid-1980s. Wages then remained largely stable until the early 1990s. From then on, wage inequality increased both at the top and the bottom ends of the wage distribution.

To explicitly quantify the contribution of changing skills to changes in the wage structure, I use a recently developed decomposition method for unconditional quantile regression models (Firpo, Fortin, and Lemieux 2007). This method has the advantages of being flexible enough to allow for changes in different parts of the wage distribution. It allows me to directly estimate how differences in one characteristic (e.g., cognitive skills) affect wages at different parts of the distribution.

My decomposition analyses show that changes in skill requirements affect workers differently because of their differing skill bundles: some experience sharp decreases in wages, while others experience sharp increases. Specifically, at the upper part of the distribution, I find that changes in skill requirements have benefitted workers with large shares of cognitive skills, but harmed workers with large shares of manual skills. In the middle of the distribution, changes in skill requirements have benefitted workers with large shares of cognitive and manual skills, but harmed workers with large shares of interactive skills. The reason why changes in skill requirements affect upper- and lower-tail inequality differently is that differently skilled workers are not uniformly distributed along the wage distribution.

Beyond their analytical relevance, my analyses are also valuable from a policy point of view, because I can clearly reject the widespread concern that wages in Germany have become polarized. I show that wages of middle-skilled workers behaved similarly to the ones of the overall population: Wages fell rather sharply at the bottom end; they increased rather sharply at the top end, and increased modestly in the middle.

Combining the research findings of the three projects reveals several important insights into what firms and individuals can do to secure returns to their educational investments and into how changing market environments might affect the realization of their returns. First, I show that firms in less regulated labor markets are well able to realize a return on their investment. By offering performance pay, they incentivize their most productive training graduates to stay, thereby recouping their training costs. Second, I show that a trade-off exists between general and specific skill bundles. While general skill bundles provide individuals with more flexibility, specific skill bundles pay a wage premium.

Third, I find that long-term returns to educational investments are crucially influenced by market dynamics. In the long run, firms want to have a workforce that is flexible and adaptive to technological changes. Similarly, individuals want to acquire skills that allow them to react to these changes. This entails regular updating of educational curricula—to ensure that graduates acquire knowledge that is at the technological frontier—as well as further training for incumbent workers to update their skill bundles.

My analyses suggest that educational curricula that are up-to-date like it is the case for Germany and Switzerland, should improve both the productivity of firms and the labor market opportunities of graduates. Indeed, while technological and structural changes have led middle-skilled workers in Anglo-Saxon countries to experience wage losses and decreases in their employment shares, middle-skilled workers in Germany were better able to react to these changes so that their wages and employment remained largely stable over the last three decades.

CHAPTER 2

Firms' Method of Pay and Investment in General Training

Part of this chapter is a revised version of early parts of the working paper "The Effect of Performance Pay on the Retention of Apprenticeship Graduates: A Panel Data Analysis" by Rinawi and Backes-Gellner (2014).

2.1 Introduction

This chapter is our first contribution in investigating the determinants of realized returns on educational investment from the firm's perspective. Specifically, we analyze how training firms that are embedded in unregulated labor markets are able to retain at least some of their trained workers to realize a return on their investment.

In the traditional human capital model (Becker 1962), firms do not invest in general training, because the associated returns accrue fully to the workers. However, a particular feature of the dual vocational education and training (VET) system is that training firms offer and pay for the general training of their apprentices. The latest cost-benefit analyses show that about 70 percent of German training firms and more than 40 percent of Swiss training firms incur net costs of training (Wolter and Strupler Leiser 2012; Jansen et al. 2015).

Harhoff and Kane (1997) started the discussion on this empirical puzzle and explained a firm's incentive to offer general training through the existence of imperfect labor markets. Acemoglu and Pischke (1998) formalized a model of this idea. The main assumption of this model is that frictions in the labor market provide training firms with a certain market power that prevents the firms' graduates from switching employers without losing income. In recent years, a large number of studies has identified different sources of labor market frictions and tested their impact on a firm's willingness to offer and finance training[1] (Acemoglu and Pischke 1998, 1999a, 1999b; Katz and Ziderman 1999; Booth and Bryan 2007; Dustmann and Schoenberg 2007, 2009; Mohrenweiser and Backes-Gellner 2010).

To date, surprisingly little discussion exists on whether factors other than imperfect markets might exist that enable training firms to retain their graduates. In this chapter, we fill this gap by exploring a potential solution that firms create internally and that does not rely on external market conditions. We use findings from personnel economics and hypothesize that firms use performance pay to incentivize their most productive graduates to stay.

We argue that for the most productive graduates the reasons to stay with their training firms are twofold: First, they expect a higher compensation because performance pay rewards their individual productivity. However, since this would also be the case for non-training firms that offer performance pay, there has to be another productivity advantage that incentivizes graduates to stay. The second reason is that they expect to gain from positive externalities from training, which do not exist in non-training firms. Recent studies show that training firms are on average more productive than non-training firms. The higher productivity can be explained through training firms' success of attracting and retaining a more productive workforce through better signaling and screening mechanisms (Autor 2001; Cappelli 2004; Backes-Gellner and Tuor 2010).

If training firms offer performance pay and the most productive graduates have an incentive to stay, then the overall productivity level is boosted even more, i.e., high quality training creates a self-reinforcing productivity advantage. Therefore, the most productive graduates should reach their highest productivity level with the current training firm, implying that expected earnings are also highest with the current training firm. In turn, training firms that use performance pay should be more successful in retaining training graduates than training firms not using it.

Going further, one could argue that these performance pay firms should also be more likely to invest in training, because they have better chances of realizing a return on their investment. Switzerland provides the most suitable setting to test our hypothesis for two main reasons. First,

[1] Training firms follow either a substitution strategy or an investment strategy. Substitution firms use apprentices as cheap substitutes for unskilled or semi-skilled workers and have no incentive in retaining them at the end of the training period (Harhoff and Kane 1997; Mohrenweiser and Backes-Gellner 2010). Investment firms invest in their apprentices, incur higher training costs and want to retain at least some of their graduates. Our analysis focuses on the latter firms.

Switzerland has a large institutionalized VET system, where training is mostly in general skills, and largely financed by training firms. Second, in contrast to other countries with a strong VET tradition like Germany, the Swiss labor market is much less regulated (Muehlemann and Wolter 2011; Ryan et al. 2013). Therefore, Swiss firms may be less able to rely on market frictions and instead need to find another way of retaining their graduates.

For the empirical analysis, we use the Swiss Earnings Structure Survey, a representative employer-employee survey. Although the survey is designed as a cross-section, we are able to identify most firms in subsequent points in time and construct a firm panel for the years 1998 through 2004. The main advantage of this data is that it contains separate information about the base and the bonus payments of individual workers, enabling us to investigate the effect of both the incidence and the magnitude of performance pay. We develop two measures for the use of performance pay in a firm, one reflecting the intensity, i.e., the amount of performance pay in relation to the total pay in a firm, and the other reflecting the coverage rate, i.e., the share of workers receiving performance pay.

To establish a causal link between a firm's use of performance pay and its ability to retain VET graduates, we run IV estimations. We instrument the performance pay measures with a variable measuring the occupational position of single workers, arguing that the position should be correlated with performance pay but should not have any effect on the retention of graduates. We find that training firms with pay-for-performance plans have a significantly higher retention of VET graduates than training firms with fixed salaries. Both the performance pay intensity and the coverage rate have a significantly positive effect on the retention of VET graduates.

This chapter contributes to the new training literature by providing an additional answer to the question of why firms would provide and pay for investment in general training. We argue and provide evidence that imperfect labor markets might not be the sole condition for the existence of firm-provided general training. Instead, our findings show that training firms in weakly regulated labor markets might resort to different payment strategies to incentivize their graduates to stay. This finding should be of high interest to policy makers who are considering the introduction of a Germanic-style dual VET system as a means to tackle youth unemployment.[2] Policy discussions should not exclusively focus on market regulations, but also account for the firm itself and potentially successful firm strategies.

[2] Empirical evidence suggests that a dual VET system smoothens youths' entry into the labor market (Bell and Blanchflower 2010; Scarpetta, Sonnet, and Manfredi 2010).

2.2 Theoretical Background

In this section, we first give a short overview of the new training literature and the performance pay literature. We then introduce a simple two-period retention model similar in spirit to Lazear (1986). Because this model does not make any assumptions concerning markets and institutions, its validity is not limited to the Swiss case. Rather, similar to Lazear's performance pay model, our retention model has general appeal.

2.2.1 Related Literature

The standard theory of training draws a crucial distinction between general and specific training (Becker 1962). While general training increases workers' productivity in many firms, specific training increases their productivity only in the firm providing training. Under the assumption of perfectly competitive labor markets, general training is solely beneficial to the worker, because it directly translates into higher wages. Therefore, Becker (1962) predicts that firms will never pay for general training.

The empirical evidence is, however, difficult to reconcile with this model. In many countries with a dual VET system, firms provide and pay for training that is largely general (von Bardeleben, Beicht, and Fehér 1995; Schweri et al. 2003; Beicht, Walden, and Herget 2004). The new training literature relaxes the assumption of perfect markets and argues that market imperfections provide training firms with a certain market power that prevents their graduates from switching employers without losing income.

A large number of studies has identified different sources of market frictions: Some contributions point out that regulations such as employment protection and institutions such as unions increase a firm's ability to retain a sufficiently high number of graduates (Acemoglu and Pischke 1999b; Dustmann and Schoenberg 2007, 2009; Jansen et al. 2012). Other studies focus on mobility costs and low labor turnover rates caused by residential inertia (Stevens 1994; Harhoff and Kane 1997), on information asymmetries (Acemoglu and Pischke 1998; Katz and Ziderman 1999; Mohrenweiser, Wydra-Sommaggio, and Zwick 2015), on reputation aspects and social expectations (Sadowski 1980; Harhoff and Kane 1997), and on complementarities between general and firm-specific training (Franz and Soskice 1994; Kessler and Luelfelsmann 2006).

Although they may well affect investment in human capital, the new training literature does generally not discuss the role of payment methods. Contrarily, personnel economics has traditionally focused on a firm's compensation structure as a means to hire and retain workers.

Starting with Lazear (1986), a growing body of evidence has shown that performance pay, defined as pay tied to worker output, has two effects. First, the incentive effect causes performance pay workers to work harder. Second, the sorting effect causes more able workers to select and stay with performance pay firms, while less able workers leave performance pay firms.

In equilibrium, workers have reallocated according to their ability so that productivity and wages in performance pay firms are higher than in fixed salary firms (Lazear 1986, 2000, 2004; Gielen, Kerkhofs, and van Ours 2009; Dohmen and Falk 2011). Thus, one stylized fact that emerges from these studies is that performance pay induces workers' selection into the right jobs. In the next section, we sketch a simple model on how this selection process might work for workers graduating from vocational education and training.

2.2.2 Retention Model

The following two-period model applies the same basic assumptions as in Lazear (1986): Firms and workers are risk-neutral and form a principal-agent relationship. Firms maximize expected profit and workers maximize expected utility. Firms can choose between two compensation strategies. They either pay a salary $w_t = S$, where w_t equals the wage the worker receives in period t and is a fixed amount, or they pay $w_t = f(q_t)$, where q_t is the output the individual worker produces in period t. There is no discounting between periods. For simplicity, in our model, we assume that firms do not incur monitoring costs.[3]

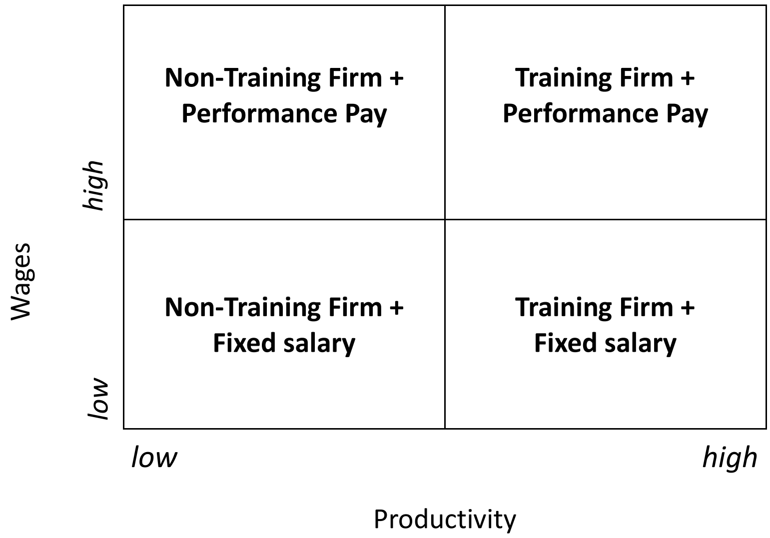
The structure of the model is as follows. In period one, the firm hires apprentices and starts training them. We assume that apprentices are randomly assigned to training firms such that each firm has a group of apprentices that are similar in their ability distribution. This is a reasonable assumption given that we know from previous research that apprentices' initial choice of training firm is random (Oswald and Backes-Gellner 2014). We also assume that firms train more apprentices than they have vacancies to fill.[4]

In period two, firms offer employment contracts to their graduates and the graduates have to decide whether to stay with their training firm or to choose a different employer. Graduates accept the employment offer if the expected compensation at their training firm is larger than their outside options. To sketch these options, we have to take into account two firm

[3] In practice, most jobs fit somewhere in between these two extremes, meaning that many employees receive a large proportion of their compensation as a fixed amount and some bonus payment depending on their output. This does not harm our model. The most important distinction between the two payment types is indeed whether or not there is some kind of variable component.
[4] Indeed, the average retention rate is 36 percent in Switzerland (Schweri et al. 2003).

characteristics, training firms and non-training firms as well as salary firms and performance pay firms. Figure 2.1 illustrates the types of firms we are considering.

Figure 2.1: Relative wages and productivity between firms



Notes: Authors' illustration.

First, we discuss the differences in expected compensation at training firms and non-training firms. As we have pointed out previously, training firms are on average more productive than non-training firms (Autor 2001; Cappelli 2004; Backes-Gellner and Tuor 2010). Since more productive firms pay higher wages (Abowd, Kramarz, and Margolis 1999), accepting the employment offer will always lead to a higher utility level than renouncing it and starting to work at a non-training firm. Thus, graduates should always prefer working at a training firm to working at a non-training firm. Indeed, in line with our prediction, Mohrenweiser (2013) shows that almost all inter-firm movement of training graduates in Germany takes place between training firms. Non-training firms hardly participate in the post-graduation recruitment market. It is thus plausible to assume that graduates switch mainly between training firms.

Second, we discuss the differences in expected compensation at training firms with performance pay and at training firms with fixed salaries. In this case, we assume that the graduates react in the same way as the incumbent workers in Lazear's (1986) model and derive the following sorting result: Graduates with $f(q_t) > S$ choose to work at a performance pay firm, while those with $f(q_t) < S$ choose firms with the fixed salary S. Therefore, for the most productive graduates, accepting the offer from a training firm with performance pay will always yield a higher utility than leaving and starting to work at a training firm with fixed salaries.

In our model, the only option yielding the same utility is an offer from a training firm with performance pay. However, because each firm trains more apprentices than it wishes to recruit, these firms already have a sufficiently high number of graduates they want to retain and do not have any incentives to hire graduates from external firms, engaging in potentially costly poaching activities.[5]

In equilibrium, these training firms with performance pay should be able to retain the most productive graduates. Given that all training firms' interests are to hire the most productive graduates only, we should observe that training firms with performance pay have a higher share of retained graduates than training firms with fixed salaries, because they offer the most attractive compensation for these graduates.

In the empirical investigation of our hypothesis we will thus compare training firms with performance pay and training firms with fixed salaries and expect to find that performance pay firms have a higher share of retained graduates than fixed salary firms. Before proceeding to the empirical analysis, we introduce the data and provide a short overview of the Swiss dual vocational education and training system. Understanding the main features of this system is crucial for interpreting the empirical results of this chapter.

2.3 Institutional Background and Data

In this section we first overview our main data, the Swiss Earnings Structure Survey. Second, we explain how we construct our dependent and the independent variables. To better understand our measurements, we also provide some key information about the Swiss VET system. Third, we present our sample and descriptive statistics.

2.3.1 The Swiss Earnings Structure Survey

For our empirical analysis, we use the Swiss Earnings Structure Survey (SESS), an employer-employee survey that is conducted every two years by the Swiss Federal Statistical Office (SFSO). The SFSO ensures representativeness of the sample by randomly drawing firms from the Swiss central register of firms within groups based on size, geographical location, and industry. Participation in the survey is compulsory. Firms with fewer than 20 employees must report on their entire workforce, firms with fewer than 50 employees on at least half of their workforce, and firms with more than 50 employees, on at least one third of their workforce.

[5] As Acemoglu and Pischke (1998) show, an additional explanation for why outside firms might not engage in poaching activities is the winner's curse.

Firms not reporting their entire workforce randomly select the employees for whom they provide data.[6] While we are able to identify firms that are being surveyed over several waves, we cannot identify single individuals that are being surveyed multiple times precisely because most firms do not report on all of their employees. Therefore, we cannot conduct any duration analyses on the individual level, but have to conduct firm-level analyses.

The SESS is particularly suitable for our analysis for three main reasons. First, the SESS is the only Swiss dataset that contains separate information about the base and the bonus pay of individual workers, enabling us to investigate the effect of both the incidence and the magnitude of performance pay.[7] Second, the SESS is an establishment survey, i.e., personnel officers fill out the questionnaire. Since the data come from establishment records they are not subject to recall error and clustering at round figures typically observed in earnings data (Zweimueller 1992). Third, the sampling has two levels, firms and individual workers. We have firm-level information such as firm size, industry[8] and location, as well as detailed information about individual worker characteristics.

To conduct the panel study on the firm level, we aggregate the individual worker data to the firm level and generate a firm panel that allows controlling for time-specific and firm-specific effects. In the analysis, we use the waves from 1998 through 2004. Even though later waves of the SESS are available, we can only use the data until 2004. Unfortunately, from 2006 onwards the firm identifier has changed so that we cannot match firms over time anymore.

2.3.2 Measurements

VET Graduates

Our dependent variable is the rate of internal VET graduates, relating the number of graduates that received their training with their current firm to the total number of workers with a VET degree in that firm. The graduates in our sample have taken part in a dual vocational education and training program. Apprentices who attend such training spend between one to two days per week in a public vocational school and three to four days at the training firm where they receive on-the-job training and take actively part in the firm's production process.

[6] The survey guidelines instruct firms that report data on part of their employees to sort them by family name or social security number and to report data on every second or every third employee in the sorted list.
[7] The SFSO combines information on earnings and working time to compute a standardized monthly wage corresponding to the earnings of an employee working 4.3 work weeks per month at 40 hours per week (Graf 2006). Since the SESS reports the four components included in the standardized monthly wage separately, simple computations allow decomposing it into a standardized base pay and a standardized bonus component.
[8] The sectors are defined according to NOGA 2002, the official general classification of economic activities used in Switzerland.

Apprentices typically start their training after compulsory schooling, when they are on average 17 years old.[9]

The two main types of training last either three or four years. Therefore, graduates are between 20 and 21 years old at the end of their training. The apprentices graduate after passing both a practical and a theoretical examination. They receive a federal certificate that is recognized throughout Switzerland. Because their skills are externally assessed, graduates have a qualification that is portable and the opportunity to move to different employers. The employment relationship ends automatically upon the completion of training and any extension must be negotiated in a new contract.

To identify those workers who have recently graduated at the firm where they are currently employed, we use three pieces of information, namely a worker's education, age and tenure. The SESS records tenure in a firm starting from the very first day of the VET program. Therefore, any worker (i) with a VET degree, (ii) who is not older than 21 and (iii) who has been working at the same firm for at least three years, has probably received his training with his current firm. Formally, we apply the following equation for each person i with a VET degree:

$$age_i - tenure_i \leq 17 \; s.t. \, age \leq 21 \tag{2.1}$$

We construct a dummy with the value one for those workers who fulfill these criteria and call it the "internal VET graduates dummy." Because this dummy does not capture the 30 percent of workers who were 18 years and older when they started their VET training, we argue that it is a conservative measure, capturing the lower bound of internal VET graduates.[10] For the sake of inference we decide to use this lower bound.[11]

In the next step, to construct the within-firm rate, we sum up the internal VET graduates dummy and divide it by the number of workers with a VET degree ("VETworkers") in that firm. Because the SESS contains only information on core workers but not on apprentices, we cannot relate the number of graduates who stay to the overall number of former apprentices within a firm, which would give us the more commonly used retention rate. We use the number

[9] The SFSO has provided us with representative data on the starting age of apprentices. In 2012, around nine percent of first-year apprentices were 15 years old, 23 percent were 16 years old, 38 percent were 17 years old, and 30 percent were 18 years old and older.

[10] We cannot enlarge our inequality to 18 or more because then we might erroneously categorize those individuals as internal graduates who graduate from the VET program at 18 years of age and switch firms right after graduation.

[11] In the empirical analysis, we run robustness checks where we modify the above equation and use a different bound. This modification does not change our main findings.

of VET workers instead, which should be a good indicator for the number of apprentices i.e., graduates within a firm. While this ratio is not a "true" retention rate, it approximates it in the best possible way. We call this ratio the rate of internal VET graduates. A thorough inspection of the data shows that throughout the observation period the fluctuations in firm size and number of VET workers are very low and, more importantly, they move in parallel.

Performance Pay

The SESS has the unique feature that it provides separate information on the base and bonus components of workers' earnings.[12] This characteristic enables us to investigate the effect of both the incidence and the magnitude of performance pay. Since we are interested in firm level outcomes, we aggregate the individual information to the firm level.

To measure the magnitude, we add up the individual performance pay amounts that VET workers receive within a firm. To generate a performance pay rate, we relate this aggregated amount of performance pay to the aggregated monthly wage of VET workers. We call this measure "performance pay intensity," because it shows the percentage of total pay that is based on performance. Formally, we define the performance pay intensity of a firm j as:

$$PP - intensity_{ij} = \frac{\sum_{i=1}^{N}(ln(monthly\ performance\ pay\ of\ VET\ worker\ i\ in\ firm\ j))}{\sum_{i=1}^{N}(ln(monthly\ gross\ wage\ \ of\ VET\ worker\ i\ in\ firm\ j))} \tag{2.2}$$

For a second measure, we construct a dummy variable indicating whether a VET worker has received performance payments. Again, because we are interested in firm level outcomes, we add up the dummy variable to see how many VET workers receive performance pay within a firm. We divide this number by the total number of workers to construct a measure for the share of workers receiving performance pay within each firm. Thereby, we use the number of workers for which we have valid wage data in the denominator. We call this measure "performance pay coverage," because it reflects the percentage of workers within a firm receiving performance pay. Formally, we define performance pay coverage of a firm j as:

$$PP - coverage_{ij} = \frac{\sum_{i=1}^{N}\ VET\ worker\ i\ receiving\ performance\ pay\ in\ firm\ j}{\sum_{i=1}^{N} worker\ i\ in\ firm\ j} \tag{2.3}$$

[12] The SESS breaks earnings down into the following parts: gross earnings, social security contributions, extra payments (including payments made for shift work, night work, weekend work, and overtime), and bonus payments, the amount of performance pay.

Controls

In addition to the above earnings data, the SESS contains a rich set of worker-level control variables. For each firm and year we use the following control variables: monthly gross wages of VET workers (fixed salary without bonus payments), age and age squared (in years), tenure and tenure squared (in years), occupational tasks (categorical), job requirements (categorical), gender (dummy), and nationality (dummy). We aggregate these individual-level variables to the firm level and compute the mean of these variables at the firm level. Importantly, we do not exclude workers by educational degree when aggregating our control variables. We also control for firm size (continuous), industry, geographical location, and year (all dummies).

2.3.3 Sample and Descriptive Statistics

We restrict our sample as follows: We exclude firms in the public sector, because they usually do not behave in a profit-maximizing way, which can have consequences for their training and retention decision (Muehlemann et al. 2007). We also exclude some firms that appear to be switching industries due to inconsistencies in the data. In addition, we drop firms in the agricultural sector because the observations in our sample are not representative (Janssen et al. 2016).

In line with previous literature, we exclude firms with fewer than five employees, because their expansion potential through hiring new graduates is very limited (Muehlemann et al. 2007). We also exclude part-time workers. Finally, since we want to explore the effect of performance pay on the retention of graduates, we compare training firms offering performance pay with training firms offering fixed salaries. In line with Mohrenweiser and Backes-Gellner (2010), we define a training firm following an investment strategy as a firm that has retained at least one graduate during the observation period.

After creating the panel and removing missing variables, we are left with a sample of 16,718 observations. Table 2.1 provides descriptive statistics for the aggregated variables, i.e., all variables are firm-level averages. The dependent variable, the rate of internal VET graduates is 0.4 percent, a clear indication that our measure is a lower bound of the real rate. Out of 1,000 VET workers in a firm, four are young internal VET graduates. Concerning our main explanatory variables, about 10 percent of monthly gross wages (about 630 Swiss francs) are performance pay earnings. The amount of performance pay varies greatly within and between firms with a minimum of zero and a maximum of 94 percent. On average, 10 percent of VET workers receive performance pay.

The variable "occupational tasks" describes 24 different tasks that workers perform on the job. Examples are administrative tasks, accounting, or logistics. The variable "job requirements" has four categories and describes how demanding a job is. Category 1 comprises repetitive tasks, category 2 comprises tasks that require some expert knowledge, category 3 comprises autonomous tasks, and category 4 describes tasks with the highest level of expert knowledge. The variable "occupational position" has five categories, ranking from 1 (positions without any management function) to 5 (the highest management position). Given that we use firm-level averages for our calculations, we include these categorical variables as continuous variables in our regression.

The average worker earns a monthly gross wage of 6,270 Swiss francs, is 41 years old and has 10 years of tenure. Average wages for VET workers figure so low in the descriptives, because all non-VET workers are assigned a wage of zero (to prevent missing values), which pushes down the mean. Sixty percent of the workforce is Swiss and 75 percent is male. The very high percentage of male workers is due to the exclusion of part-time workers.

Table 2.1: Descriptive statistics

Variables	Obs.	Mean	St. Dev.	Min	Max
Internal VET graduates	16,718	0.004	0.019	0.0008	0.3333
Performance pay intensity	16,718	0.097	0.165	0	0.9358
Performance pay coverage	16,718	0.102	0.189	0	1
Wage	16,718	6,270	2,242	1,735	52,526
VET Wage	16,718	1,048	2,453	0	23,095
Occupational tasks	16,718	20.89	7.742	10	40
Occupational position	16,718	3.855	1.023	1	5
Job requirements	16,718	2.233	0.725	1	4
Tenure	16,718	10.18	5.459	0	48
Age	16,718	41.08	5.851	18	64
Male	16,718	0.752	0.270	0	1
Swiss	16,718	0.602	0.322	0	1
Firm size	16,718	180.9	691.2	5	32,000
Industry	16,718	7.081	3.286	3	15
Region	16,718	3.631	1.858	1	7

Notes: Swiss Earnings Structure Survey, 1998-2004. Based on authors' calculations.

2.4 Empirical approach

In this section, we first explain how we identify the causal effect of performance pay on the retention of internal VET graduates. Because of a potential endogeneity bias, we instrument our performance pay measures with a variable measuring a worker's occupational position.

The rationale of the IV strategy is that the occupational position should be correlated with both the amount of performance pay and the likelihood of receiving it. It should, however, be uncorrelated with the retention of internal VET graduates. Second, we present our estimation approach, moving from pooled OLS to firm fixed effects and finally to panel IV estimations.

2.4.1 Identification Strategy

Our model predicts that performance pay has a positive impact on a firm's ability to retain its most productive graduates. A convincing analysis of the causal link between performance pay and the retention rate requires an exogenous source of variation in performance payments. It is conceivable that exogenous demand shocks might influence both a firm's payment and retention strategies. Positive demand shocks induce an upward bias if they cause firms to increase their recruitment and retention of apprentices to cope with increased needs for skilled labor and, simultaneously, cause firms to increase their performance payments due to increased profits. In contrast, low performance payments might be a signal for labor costs problems that the firm might try to solve by a hiring stop.

A consistent estimate of the true effect can be obtained if there is a component of the vector X_i that affects performance payments but not directly the retention of internal training graduates. We need to identify a causal determinant of performance pay that can be legitimately excluded from the regression equations. The occupational position might be such a variable. In our dataset, occupational position is a categorical variable with five categories.

Workers belong to either one of the following categories: (5) upper management, (4) middle management, (3) lower management, (2) lowest management, and (1) no management function. Simple correlational analysis reveals that the higher the occupational position, the more likely it is that workers receive performance pay. The occupational position should thus affect the amount and incidence of performance pay. However, the instrument can be excluded from the outcome equation given that these young graduates are mostly in category (1) as they are at the beginning of their career. We thus assume that the occupational position can be omitted from our regression equations, since the direct role of occupations is adequately captured by the regressors "job requirements" and "occupational tasks."

2.4.2 Estimation

The function that has to be estimated can be specified as follows:

$$y_{jt} = \alpha_j + \beta * PP_{jt} + x'_{jt} * \gamma + \varphi_r + \varphi_i + \varphi_t + \varepsilon_{jt}, \tag{2.4}$$

where t is a time indicator and j is a firm indicator, y_{jt} is the share of internal VET graduates, PP_{jt} is the main explanatory variable, performance pay intensity in model I and performance pay coverage in model II. x'_{jt} is a vector of control variables, and φ_r, φ_i, φ_t are controls for region, industry, and year. ε_{jt} is the error term, which is assumed to be mean zero and normally distributed. We call this function the "graduates equation."

The control vector x'_{jt} includes wages, age and tenure and their squared terms, a job requirements measure, an occupational tasks measure, gender and nationality dummies, and firm size. We include wages of VET workers (measuring the base payments without performance pay) as control variable to ensure that our PP-variables are not simply capturing wage effects, i.e., it is not only the higher wage that induces graduates to stay. Because our dependent variable is bound between 0 and 1, we winsorize our data, replacing the highest and lowest values with 0.001 and 0.999 respectively (Cox 2006).

To begin the investigation of the effect of performance pay on the retention success, we run pooled OLS regressions. However, with pooled OLS we consider observations of the same firm in different years as independent and we do not take unobserved firm heterogeneity into account. Therefore, this regression is potentially biased. Most firms have unobserved characteristics that influence both a firm's payment strategy and the rate of internal training graduates. One example is a firm's productivity level, because a higher productivity leads to higher performance pay rates, and at the same time to higher training endeavors.

To overcome time invariant unobserved heterogeneity, we use the panel structure of our data and estimate firm fixed effects regressions. Equation (2.5) shows our second specification. The firm fixed effect, φ_j, captures the impact of time-invariant differences among firms in observed and unobserved characteristics.

$$y_{jt} = \alpha_j + \beta * PP_{jt} + x'_{jt} * \gamma + \varphi_j + \varphi_t + \varepsilon_{jt} \tag{2.5}$$

However, as argued previously, endogeneity might bias our fixed effects regressions. Therefore, in the third step, we apply an IV approach and use the occupational positions as an instrument for performance pay. We estimate the following two-equation system with 2SLS:

First stage:

$$PP_{jt} = \alpha_j + \beta * OP_{jt} + x'_{jt} * \gamma + \varphi_j + \varphi_t + \varepsilon_{jt} \tag{2.6}$$

Second stage:

$$y_{jt} = \alpha_j + \beta * \widehat{PP}_{jt} + x'_{jt} * \gamma + \varphi_j + \varphi_t + \varepsilon_{jt} \tag{2.7}$$

2.5 Results

Tables 2.2 and 2.3 report the results of the pooled OLS with clustered standard errors for model I and model II respectively. In specification (1), we regress the retention variable on our performance pay measures without including any controls. In specification (2), we estimate the full model with all controls. The results show that both the performance pay intensity (PP-intensity) and the performance pay coverage (PP-coverage) have a positive and statistically significant effect on the rate of internal VET graduates.

To interpret the effect size, we need to keep in mind that our dependent variable and our main explanatory variables are proportions. The coefficients of these variables can be interpreted in terms of a percentage change in the rate of internal VET graduates. In the full model, a ten percent increase in PP-intensity increases the rate of internal VET graduates by 0.12 percent. Similarly, a ten percent increase in PP-coverage increases the rate of internal VET graduates by 0.072 percent. At first glance, this effect may seem economically unimportant. However, recall that in our sample with conservative measurements the mean rate of internal VET graduates is 0.44 percent. A ten percent increase in our PP-measures thus increases the rate of internal VET graduates from 0.44 percent to about 0.4405 percent. With a ten percent increase in PP-intensity or PP-coverage, the number of internal VET graduates thus increases from 4.4 to 4.5 workers per 1000 VET workers. Since the true rate is potentially larger, so is the true effect size. Indeed, in our robustness checks, where we include all internal VET graduates and not only the young ones, the effect sizes are three times larger (see Appendix Tables A.2.1 and A.2.2).

The control variables comprise individual and firm characteristics aggregated at the firm level. Size and direction of the coefficients are similar in both models. Average wages of VET workers have a small, but significantly positive effect on the rate of internal VET graduates. The variable age is U-shaped and tenure is inverted U-shaped and both are highly statistically significant. Both effects are in line with our expectations and result from our definition of internal VET graduates. Since we impose the restriction that the graduates cannot be older than 21 years, age has a negative effect on the rate of internal VET graduates with a minimum at around 46 years. Similarly, increasing tenure has a positive effect on the rate of internal VET graduates with a maximum at 16 years of tenure.

As expected, the variable "job requirements" has a significantly positive effect of the rate of internal VET graduates. With increasingly demanding tasks, the rate of internal VET graduates increases. This makes sense both from the firm's and the graduates' perspectives. Firms are eager to retain graduates who fulfill tasks that are not easily replaceable and graduates will be more inclined to stay if they have meaningful job tasks. Surprisingly, the percentage of males has a significantly negative effect of the rate of internal VET graduates. It appears that the higher the percentage of male workers, the lower the probability that graduates stay with their firm. One could derive from this result that firms should make sure to have a gender-balanced workforce to retain their graduates.

Table 2.2: Model I: Pooled OLS regression

	Rate of internal VET graduates	
	(1)	(2)
PP-intensity	0.0372***	0.0120***
	(0.0017)	(0.0017)
VET Wage		0.000002***
		(0.0000001)
Age		-0.0031***
		(0.0003)
Age squared		0.00003***
		(0.000003)
Tenure		0.0006***
		(0.0001)
Tenure squared		-0.00002***
		(0.000003)
Male		-0.0014**
		(0.0007)
Swiss		0.0003
		(0.0004)
Occupational tasks		-0.000003
		(0.00002)
Job requirements		0.0007***
		(0.0002)
Firm size	No	Yes
Industry	No	Yes
Region	No	Yes
Year	No	Yes
R-squared	0.1067	0.1728
Observations	16,718	16,718

Notes: Swiss Earnings Structure Survey, authors' calculations.
Significance levels: * < 0.1; ** < 0.05; *** < 0.01.
Clustered standard errors in parentheses.

Table 2.3: Model II: Pooled OLS regression

	Rate of internal VET graduates	
	(1)	(2)
PP-coverage	0.0286*** (0.0015)	0.0072*** (0.0015)
VET Wage		0.000002*** (0.0000001)
Age		-0.0032*** (0.0003)
Age squared		0.00003*** (0.000003)
Tenure		0.0006*** (0.0001)
Tenure squared		-0.00002*** (0.000003)
Male		-0.0017*** (0.0007)
Swiss		0.0005 (0.0004)
Occupational tasks		0.000002 (0.00002)
Job requirements		0.0007*** (0.0002)
Firm size	No	Yes
Industry	No	Yes
Region	No	Yes
Year	No	Yes
R-squared	0.0831	0.1705
Observations	16,718	16,718

Notes: Swiss Earnings Structure Survey, authors' calculations.
Significance levels: * < 0.1; ** < 0.05; *** < 0.01.
Clustered standard errors in parentheses.

As discussed earlier, pooled OLS regressions are potentially biased and might lead us to draw wrong conclusions. Exploiting the panel structure of the data, in the next step, we estimate firm-fixed effects to overcome this bias and improve our estimation results. Tables 2.4 and 2.5 report the results for the firm fixed-effects regressions with cluster-robust standard errors for model I and model II respectively. Again, we first regress our dependent variable on the performance pay measures alone and then include the control variables.

Overall, we confirm the results obtained in the pooled OLS regressions. Again, we find that both performance pay measures are highly significantly positively correlated with the share of internal VET graduates. In the full model in specification (2), a ten percent increase in PP-intensity or PP-coverage increases the rate of internal VET graduates by about 0.1 percent (0.145 and 0.111 percent respectively). This effect size is largely in line with the effect sizes from the pooled OLS regressions.

Again, average VET wages have a small but highly statistically significant positive effect on the rate of internal graduates. Age and tenure effects are similar to the OLS estimates in terms of significance and magnitude. In the fixed effects estimates, gender and job requirements do not have a significant effect anymore. Given that the results from both the pooled OLS and the fixed-effects regressions might be biased, we present a detailed discussion and interpretation of the effect sizes in our instrumental variables regressions in Tables 2.6 and 2.7.

Table 2.4: Model I: Fixed effects regression

	Rate of internal VET graduates	
	(1)	(2)
PP-intensity	0.0357*** (0.0027)	0.0145*** (0.0026)
VET Wage		0.000002*** (0.0000001)
Age		-0.0029*** (0.0004)
Age squared		0.00003*** (0.00001)
Tenure		0.0004** (0.0002)
Tenure squared		-0.00001*** (0.00001)
Male		0.0008 (0.0014)
Swiss		-0.0002 (0.0009)
Job requirements		0.00003 (0.00004)
Occupational tasks		-0.0004 (0.0004)
Firm size	No	Yes
Industry	No	Yes
Region	No	Yes
Year	No	Yes
R-squared	0.0565	0.1105
Observations	16,718	16,718
Number of firms	6,897	6,897

Notes: Swiss Earnings Structure Survey, authors' calculations.
Significance levels: * < 0.1; ** < 0.05; *** < 0.01.
Robust standard errors in parentheses.

Table 2.5: Model II: Fixed effects regression

	Rate of internal VET graduates	
	(1)	(2)
PP-coverage	0.0279***	0.0111***
	(0.0024)	(0.0023)
VET Wage		0.000002***
		(0.0000001)
Age		-0.0028***
		(0.0004)
Age squared		0.00003***
		(0.00001)
Tenure		0.0005***
		(0.0002)
Tenure squared		-0.00001***
		(0.00001)
Male		0.0007
		(0.0014)
Swiss		-0.0001
		(0.0009)
Occupational tasks		0.00004
		(0.00004)
Job requirements		-0.0003
		(0.0004)
Firm size	No	Yes
Industry	No	Yes
Region	No	Yes
Year	No	Yes
R-squared	0.0462	0.1096
Observations	16,718	16,718
Number of firms	6,897	6,897

Notes: Swiss Earnings Structure Survey, authors' calculations.
Significance levels: * < 0.1; ** < 0.05; *** < 0.01.
Robust standard errors in parentheses.

Despite their stability across specifications, the estimated performance pay coefficients in Tables 2.4 and 2.5 may give a biased estimate of the true economic effect because of potential endogeneity. It is conceivable that firms alter their qualification structure simultaneously with their profit or that both are influenced by demand shocks. A convincing analysis of the causal effect of performance pay on the rate of internal VET graduates requires an exogenous source of variation in the performance pay measures. We need to identify a causal determinant of performance pay that can be excluded from our graduates function.

We use the occupational position (OP) as an exogenous determinant of performance pay. Workers who hold managerial positions are both more likely to receive performance pay and a higher share of performance pay than workers who hold no managerial positions. Given that young VET graduates who are just starting their career do generally not hold managerial positions, one can expect OP to have no influence on the rate of internal VET graduates.

Tables 2.6 and 2.7 present the results from our IV regressions, using OP as an instrument. To investigate the relation between the instrument and the dependent variable, we first run reduced form regressions. The reduced form coefficients show that the instrument is highly statistically significant and positively correlated with the dependent variable. The coefficient is rather small; however, it is similar in size to the coefficients of the control variables. These results support the credibility of our instrument.

In the 2SLS regression, the first stage regression has high explanatory power and the OP coefficient is positive and highly statistically significant. Because we have one instrument for one endogenous variable, we cannot test for instrument validity. However, the first stage tests for instrument relevance. The value of the F-statistic of the first stage is well above 10 in both models (105.40 in model I and 213.55 in model II), so that we can confidently assume that our instrument is strong (Staiger and Stock 1997). As an additional test for weak instruments, Stock and Yogo (2005) propose a test for the just-identified case. If we are willing to tolerate distortion for a 5% Wald test based on the 2SLS estimator so that the true size can be at most 10 percent, then we reject the null hypothesis if the test statistic exceeds 16.38. The F-statistic greatly exceeds this value so that we feel comfortable in rejecting the null of weak instruments.

The second stage results show a highly statistically significant positive effect of performance pay on the retention of VET graduates. Using occupational position as an exogenous determinant of performance pay yields IV estimates of the performance pay effect of 3.86 percent for PP-intensity and 2.34 percent for PP-coverage. The 2SLS estimates are about two times larger than the corresponding OLS estimates. The standard errors of the IV estimates are obviously larger than the OLS estimates, but overall not inflated to a worrisome size. The effect of PP-intensity is almost two times larger than the effect of PP-coverage. This makes sense assuming that the decision-making would be driven more by the extra amount of money that an individual receives rather than by the likelihood that a person receives an extra amount of money.

Among the control variables, again, wages, age and tenure are significant in the second stage for both models. Aside from the likelihood of receiving performance pay, also the base pay received matters to VET graduates. As we have pointed out previously, this is in line with expectations. The most productive VET graduates decide to stay with their firm not only if they have a high chance of receiving performance pay, but, of course, also only if the base pay is attractive enough.

Overall, the results support our hypothesis. In terms of effect size, a 10 percent increase in PP-intensity causes an increase of 0.38 percent in the rate of internal VET graduates. A 10 percent increase in PP-coverage causes an increase of 0.23 percent in the rate of internal VET graduates. These effects are sizable given that our rate of internal VET graduates is 0.04 percent only. Because we are able to take into account both unobserved heterogeneity and endogeneity, the panel IV regression is our preferred estimation specification. Our results show a causal relationship between performance pay and the internal rate of VET graduates, thus that a performance pay effect exists that influences a firm's ability to retain graduates.

Table 2.6: Model I: IV regression, instrument: occupational position

	Reduced Form	First Stage	Second Stage
	Dep. Var. *intern*	Dep. Var. *PP-int*	Dep. Var. *intern*
PP-intensity			0.0386*** (0.0139)
VET Wage	0.000002*** (0.0000001)	0.000027*** (0.0000008)	0.000001*** (0.0000004)
Age	-0.0030*** (0.0004)	-0.0105*** (0.0023)	-0.0025*** (0.0004)
Age squared	0.00003*** (0.000005)	0.00010*** (0.000027)	0.00003*** (0.000004)
Tenure	0.0005*** (0.0002)	0.0051*** (0.0011)	0.0003* (0.0002)
Tenure squared	-0.00001*** (0.000005)	-0.00007** (0.000031)	-0.00001** (0.000005)
Male	0.0008 (0.0015)	-0.0176* (0.0091)	0.0014 (0.0015)
Swiss	0.0014 (0.0009)	0.0900*** (0.0079)	-0.0021 (0.0014)
Occupational tasks	0.00004 (0.00004)	0.00003 (0.00033)	0.00004 (0.00004)
Job requirements	0.00025 (0.0005)	0.0086*** (0.0032)	-0.0001 (0.0004)
Occupational position	0.0010*** (0.0004)	0.0250*** (0.0025)	
Firm size	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Region	Yes	Yes	Yes
Year	Yes	Yes	Yes
Observations	16,718	16,718	16,718
Number of firms	6,897	6,897	6,897
(Centered) R squared	0.1049	0.3230	0.0927
F-Statistic first stage	105.4	105.4	105.4
Stock-Yogo critical value	16.38	16.38	16.38

Notes: Swiss Earnings Structure Survey, authors' calculations.
Significance levels: * < 0.1; ** < 0.05; *** < 0.01. Robust standard errors in parentheses.

Table 2.7: Model II: IV regression, instrument: occupational position

	Reduced Form	First Stage	Second Stage
	Dep. Var. *intern*	Dep. Var. *PP-cov*	Dep. Var. *intern*
PP-coverage			0.0234*** (0.0083)
VET Wage	0.000002*** (0.0000001)	0.000026*** (0.0000009)	0.000002*** (0.0000002)
Age	-0.0030*** (0.0004)	-0.0155*** (0.0024)	-0.0026*** (0.0004)
Age squared	0.00003*** (0.000005)	0.00015*** (0.000029)	0.00003*** (0.000004)
Tenure	0.0005*** (0.0002)	0.0026** (0.0011)	0.0004*** (0.0002)
Tenure squared	-0.00001*** (0.000005)	-0.00003 (0.000031)	-0.00001*** (0.000005)
Male	0.0008 (0.0015)	-0.0099 (0.0093)	0.0010 (0.0014)
Swiss	0.0014 (0.0009)	0.1209*** (0.0087)	-0.0014 (0.0012)
Occupational tasks	0.00004 (0.00004)	-0.00071* (0.00037)	0.00005 (0.00004)
Job requirements	0.00025 (0.0005)	0.01202*** (0.0038)	-0.00003 (0.0004)
Occupational position	0.0010*** (0.0004)	0.0413*** (0.0029)	
Firm size	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Region	Yes	Yes	Yes
Year	Yes	Yes	Yes
Observations	16,718	16,718	16,718
Number of firms	6,897	6,897	6,897
(Centered) R squared	0.1049	0.2644	0.1028
F-Statistic first stage	213.6	213.6	213.6
Stock-Yogo critical value	16.38	16.38	16.38

Notes: Swiss Earnings Structure Survey, authors' calculations.
Significance levels: * < 0.1; ** < 0.05; *** < 0.01. Robust standard errors in parentheses.

2.6 Conclusion

This chapter examines the effect of performance pay on the retention of internal VET graduates. Being able to retain these graduates is crucial for a firm's willingness to offer and pay for general training, because it allows firms to realize a return on their educational investments. Previous studies explain a firm's training incentive with the existence of imperfect labor markets, identifying different market frictions and institutions that induce a training investment. Our explanation does not rely on labor market conditions. Instead, we explore what firms themselves might do. Applying findings from personnel economics to the theory of training, we hypothesize that training firms use performance pay to incentivize their most productive graduates to stay. Drawing on a theoretical model by Lazear (1986), we develop a simple contracting framework to provide a rationale for this firm behavior.

In the empirical analysis, we use data from a representative employer-employee survey that contains register data on the base pay and performance pay (PP) of individual workers. We construct two different PP-measures, one reflecting the share of performance pay relative to the base pay and the other one the share of workers receiving performance pay. To establish a credible causal link between performance pay and a firm's ability to retain graduates we use instrumental variable regression. As instrument, we use a variable measuring the occupational position of workers, arguing that the position should be correlated with performance pay but should not have any effect on the retention of graduates.

We find that training firms with performance pay have a significantly higher retention of internal VET graduates than training firms with fixed salaries. We are able to consistently show a causal relationship between the use of PP and the internal rate of VET graduates and thus argue that there exists a performance pay effect that influences a firm's ability to retain graduates. We contribute to the theory of training by providing an additional answer to the question of why firms provide and pay for training even if that training is general and easily marketable. . This chapter thus provides additional insights into the question of why firms offer and pay for general training. Ultimately, because retaining the most productive graduates helps covering a firm's training costs, an increased retention rate should in turn lead to a higher likelihood of offering training.

As pointed out previously, the investment decision involves two parties. Firms that offer training must of course also find workers who are willing to take the offer. Individuals decide on whether or not to participate in training depending on their expected return on investment. In the next chapter, we will focus on the returns to the individual.

2.7 Appendix

Tables A.2.1 and A.2.2 show the results of a specification where we reduce our lower bound from 17 to 16 years of age and include all internal VET graduates, regardless of their age. The formula is the following: $age_i - tenure_i \leq 16$. Results are in line with our preferred estimation, reported in Tables 2.6 and 2.7. As expected, given our less restrictive definition of internal VET graduates, the effect sizes for both measures of performance pay are much larger than for the specifications in Tables 2.6 and 2.7.

Table A.2.1: Model I: IV regression, instrument: occupational position

	Reduced Form	First Stage	Second Stage
	Dep. Var. *intern*	Dep. Var. *PP-int*	Dep. Var. *intern*
PP-intensity			0.0897*** (0.0322)
VET Wage	0.000007*** (0.0000003)	0.000027*** (0.0000008)	0.000004*** (0.0000009)
Age	-0.0030*** (0.0008)	-0.0105*** (0.0023)	-0.0020*** (0.0007)
Age squared	0.00003*** (0.000009)	0.00010*** (0.000027)	0.00002** (0.000009)
Tenure	0.0009** (0.0004)	0.0051*** (0.0011)	0.0005 (0.0004)
Tenure squared	-0.000007 (0.00002)	-0.000068** (0.00003)	-0.000001 (0.00001)
Male	0.0003 (0.0030)	-0.0176* (0.0091)	0.0018 (0.0031)
Swiss	0.0033* (0.0017)	0.0900*** (0.0079)	-0.0048 (0.0033)
Occupational tasks	-0.00003 (0.0001)	0.00003 (0.0003)	-0.00003 (0.0001)
Job requirements	0.00073 (0.0010)	0.00856*** (0.0032)	-0.00003 (0.0009)
Occupational position	0.0022*** (0.0008)	0.0250*** (0.0025)	
Firm size	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Region	Yes	Yes	Yes
Year	Yes	Yes	Yes
Observations	16,718	16,718	16,718
Number of firms	6,897	6,897	6,897
(Centered) R squared	0.1848	0.3230	0.1576
F-Statistic first stage	105.40	105.40	105.40
Stock-Yogo critical value	16.38	16.38	16.38

Notes: Swiss Earnings Structure Survey, authors' calculations.
Significance levels: * < 0.1; ** < 0.05; *** < 0.01. Robust standard errors in parentheses.

Table A.2.2: Model II: IV regression, instrument: occupational position

	Reduced Form	First Stage	Second Stage
	Dep. Var. *intern*	Dep. Var. *PP-cov*	Dep. Var. *intern*
PP-coverage			0.0543*** (0.0191)
VET Wage	0.000007*** (0.0000003)	0.000026*** (0.0000009)	0.000005*** (0.0000006)
Age	-0.0030*** (0.0008)	-0.0155*** (0.0024)	-0.0021*** (0.0007)
Age squared	0.00003*** (0.000009)	0.00015*** (0.000029)	0.00002** (0.000009)
Tenure	0.0009** (0.0004)	0.0026** (0.0011)	0.0008* (0.0004)
Tenure squared	-0.000007 (0.00002)	-0.000033 (0.00003)	-0.000005 (0.00002)
Male	0.0003 (0.0030)	-0.0099 (0.0093)	0.0008 (0.0029)
Swiss	0.0033* (0.0017)	0.1209*** (0.0087)	-0.0033 (0.0028)
Occupational tasks	-0.00003 (0.0001)	-0.00071* (0.0004)	0.00001 (0.0001)
Job requirements	0.0007 (0.0010)	0.0120*** (0.0038)	0.0001 (0.0008)
Occupational position	0.0022*** (0.0008)	0.0413*** (0.0029)	
Firm size	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Region	Yes	Yes	Yes
Year	Yes	Yes	Yes
Observations	16,718	16,718	16,718
Number of firms	6,897	6,897	6,897
(Centered) R squared	0.1848	0.2644	0.1849
F-Statistic first stage	213.6	213.6	213.6
Stock-Yogo critical value	16.38	16.38	16.38

Notes: Swiss Earnings Structure Survey, authors' calculations.
Significance levels: * < 0.1; ** < 0.05; *** < 0.01. Robust standard errors in parentheses.

CHAPTER 3

The Returns to Skill: Occupational Mobility and Wages

Part of this chapter is a revised version of early parts of the working paper "Labor Market Transitions after Layoffs: The Role of Occupational Skills" by Rinawi, Krapf and Backes-Gellner (2014).

3.1 Introduction

In this chapter, we investigate the returns to educational investments from the individual perspective. Specifically, we investigate earnings and employment opportunities of individuals with a dual vocational education and training degree (VET), putting special emphasis on the heterogeneity of skills that exists among different VET programs.

A commonly held belief in labor economics is that vocational education provides students with specific occupational skills that prepare them to work in one particular occupation. Although researchers acknowledge that the close link between teaching content and on-the-job skill requirements improves school-to-work transitions, many are concerned that these occupational skills are too narrowly defined and deprive workers of any flexibility and mobility (Krueger and Kumar 2004a, 2004b; Kambourov and Manovskii 2008, 2009a, 2009b; Hanushek et al. 2017).

These concerns make sense against the background of the early human capital theory introduced by Becker (1962), which distinguishes between skills that are either specific to a given firm or completely general. In this framework, firm-sponsored training cannot be general, because firms would never provide training in skills that are transferable. Therefore, the skills acquired during vocational education must be specific to the firm and workers are tied to their initial firm.

However, the traditional human capital model has been extended over the last three decades, mostly in response to empirical findings that cannot be easily reconciled with Becker's early predictions. It has been shown that general skills are an important component of the dual VET programs that exist in German-speaking countries (von Bardeleben, Beicht, and Fehér 1995; Schweri et al. 2003; Beicht, Walden, and Herget 2004). More precisely, these VET countries are characterized by occupational labor markets, which are structured along corresponding tracks of vocational qualifications and bound by vocational qualifications (Maurice, Sellier, and Silvestre 1982; Eyraud, Marsden, and Silvestre 1990; Marsden 1999). The skills acquired during VET are indeed specific to a certain vocational occupation, but can still be of use outside that occupation. Therefore, to make any predictions about the mobility of VET graduates it is imperative to first conceptualize how to define the specificity of their training.

In this chapter, we draw on the "skill-weights approach" introduced by Lazear (2009). He assumes that all skills are general in nature but firms use skills in different combinations with different weights. His skill weights approach provides an ideal foundation to operationalize the specificity of dual vocational education and training programs (Mure 2007). Adopting his idea, we characterize VET occupations by bundles of single skills and build occupation-specific skill weights to measure their degree of specificity. We distinguish workers according to the degree of specificity of the occupation they were trained in. Throughout this chapter, we will refer to workers who received training in more specific occupations as "workers in more specific occupations" and we do the same for workers who received training in more general occupations.

We investigate whether, and if so, how the degree of specificity determines worker mobility. We define mobility as the ease with which workers switch their occupation. We thus investigate which groups of workers are more likely to switch occupations and how these switches affect their wages. For this type of analysis, distinguishing between layoffs and quits is crucial (Lazear 2009). While layoffs are initiated by the firm and are supposed to reflect the choice of the firm, quits are an outcome of worker's choice. Whereas quitting is a deliberate decision, being laid off is not and it often happens unexpectedly. Workers can always decide against quitting and instead staying with their old employer, but they cannot decide against being laid off. The analysis of how well VET prepares workers for coping with layoffs is particularly valuable, because it provides information about the riskiness of a worker's educational investment. Therefore, we decide to focus our analysis on laid-off individuals.

These individuals have four different options to react to the layoff: They may find reemployment in the original occupation, find reemployment in a different occupation, remain unemployed, or quit the labor force. We summarize these four options with the term "labor market transitions." We estimate the probability of these labor market transitions as a function of a worker's degree of specificity. With this approach, we do not only investigate whether or not workers in more specific occupations switch less frequently, but we also analyze whether these workers have to wait longer for a suitable match. We expect that workers in more specific occupations are less mobile, meaning that they are less likely to switch occupations and more likely to stay unemployed for a longer time than workers in more general occupations.

Relating specificity to wages, Lazear (2009) argues that workers have higher wages and suffer larger wage losses in firms that require specific skill combinations. In our model, this implies that workers in more specific occupation have higher wages and suffer larger wage losses than workers in more general occupations. To test these hypotheses, we proceed in two steps. First, we estimate an earnings equation with occupational specificity as the main explanatory variable and wages in the original occupation as the dependent variable. We expect to find a positive relationship between specificity and wages. Second, we repeat the exercise using the smaller sample of reemployed individuals. Now, our dependent variable is the change in wages between the original and the new occupation. We expect to find a negative relationship between specificity and wage changes.

Finally, we investigate the transferability of skills in more detail. Lazear's model posits that, the more idiosyncratic a firm is in its skill requirements, the higher are the expected wage losses its workers suffer upon layoff. Put differently, the extent of the expected wage loss depends on the proportion of skills workers can transfer from one firm to the other. Transferring Lazear's model to the level of occupations, wage losses depend on the proportion of skills workers can transfer from one occupation to the other.

Recent contributions investigating the transferability of skills introduce the concept of "skill distance" to measure the proportion of skills that is transferred during an occupational change (Poletaev and Robinson 2008; Gathmann and Schoenberg 2010; Robinson 2011). They provide an empirical measure for comparing two occupations in terms of their underlying skill bundles. This measure is a useful empirical tool to estimate wage changes resulting from occupational changes. However, the skill distance literature does not provide a theoretical explanation for why certain workers change their occupation and others do not; it does not account for the number of job offers workers have.

We use Lazear's comprehensive skill-weights approach to derive our hypotheses and use the skill distance measure to test one of these hypotheses empirically, namely that the extent of wage loss depends on the proportion of skills that is transferred. If we combine Lazear's model with the skill distance measure, we can thus provide a thorough explanation for the observed patterns of both occupational mobility and wage changes.

Empirically, we focus on short-term effects and investigate labor market transitions one year after the layoff. We combine data from the *Berufsinformationszentrum* with the Social Protection and Labour Market (SESAM) survey. The first data set provides a detailed list of skill requirements for all vocational occupations in Switzerland. The second data set is a representative worker survey conducted by the Swiss Federal Statistical Office. We use the SESAM for two main reasons. First, its panel structure allows following workers over time to track their labor market transitions. Second, the survey is linked with register data on wages and unemployment benefits. The administrative nature of this data minimizes measurement error in wages and occupational coding.

Our empirical analyses confirm our hypotheses. We find that occupational specificity crucially determines worker mobility. The more specific the occupation, the less likely the worker finds reemployment in a different occupation after being laid off. Moreover, the more specific the occupation, the more likely the worker stays unemployed for a prolonged time. Regarding wages, our results show that a higher occupational specificity is indeed associated with higher wages. In addition, we find that the higher the occupational specificity, the larger the drop in wages. Finally, we show that the larger the skill distance between two occupations, the higher the wage loss for workers who change between these occupations. Taken together, these findings suggest a risk-return trade-off for investments in more specific skill bundles. While workers in more specific occupations are less mobile than workers in more general occupations, they are compensated for their lower mobility with higher wages.

Our analyses show that single skills and the bundling of these skills crucially determine workers' mobility and wages. The advantage of this new skill-weights view is that it provides a convincing explanation for the mobility differences we observe in the data. In addition, this new approach helps to better understand the observed patterns in wage changes after an occupational change. They are consistent with the idea that single skills are transferable across occupations and that the transferability of skill bundles depends on the skill weights.

3.2 Theoretical Framework

In this section, we first present the skill weights approach proposed by Lazear (2009) and derive empirically testable hypotheses regarding workers' mobility and wages. Then, we introduce a relatively new concept in the mobility literature, the "skill distance." This concept allows an empirical assessment of how similar two occupations are in terms of their underlying skill bundles. We distinguish occupational changes according to how different the skill bundles are between the original occupation and the new occupation and relate the resulting changes in wages to the skill distance.

3.2.1 Skill Weights Approach

Lazear (2009) proposes a new theory of human capital that puts emphasis on the individual composition of skills. While standard human capital theory strictly distinguishes between general and specific human capital, Lazear's skill-weights approach assumes that all skills are general in nature. However, firms vary in their weighting of different skills. In his basic model only two skills (*A* and *B*) and two periods exist. Firms use the general skills *A* and *B* in different combinations, with firm-specific weights attached to them. Specificity, therefore, occurs because firms demand different combinations and different weights of skills.

The investment problem for the worker in this set-up is to choose a strategy that maximizes net expected earnings while taking into account that different firms demand different types of skill combinations. In the first period, a worker decides on a particular skill bundle composed of the skills *A* and *B*. Workers acquire skills at cost $C(A, B)$ with $C_A, C_B \geq 0$ and $C_{AA}, C_{BB} < 0$. In the second period, the worker's pay-off at firm i is determined by the simple earnings function $Y_i = \lambda_i A + (1 - \lambda_i)B$, where $0 \leq \lambda \leq 1$ is the relative weight of skill *A* in firm *i*. The weight λ is particular to each firm and has density $F(\lambda)$.

A novel empirical implication of Lazear's model is that occupational mobility and wage changes depend on the market weight, $F(\lambda)$. The market weight determines by how much the investment will depreciate. If the difference between the weight of the initial firm and the market weight, $(\lambda_i - \bar{\lambda})$, is small, then the worker is more likely to find a firm that uses a skill combination similar to his own. In this case, his skill combination is rather general. If the difference, $(\lambda_i - \bar{\lambda})$, is large, then the skill combination is rather specific.

If a worker were certain to remain with his initial firm indefinitely, he would invest in the particular skill bundle that maximizes the payoff in that firm. Lazear's model, however, allows for separations. Because other firms might demand a different weighting of skills *A* and *B*, the worker's initial skill bundle might not be optimal in another firm, making part of his initial investment worthless. In case of a layoff, the worker might thus face a wage loss.[1]

Translating Lazear's idea of firm-specific human capital to the level of occupations, we argue that each occupation *j* requires a different combination of single skills with occupation-specific weights, λ_j, thereby further developing an idea first applied by Geel, Mure, and Backes-Gellner (2011).[2] We characterize occupations by skill bundles and determine their specificity by comparing them to the market weight, $\bar{\lambda}$. We then explore how occupational specificity determines mobility and wage changes of laid-off workers.

When workers are laid off, they have four options: finding reemployment in the original occupation, finding reemployment in a different occupation, remaining unemployed or leaving the labor force (Blanchard et al. 1990). In his model, Lazear assumes that the value the worker gets from a new job is always greater than the value of unemployment or being out of the labor force Therefore, if the worker receives a job offer, he always accepts it. In our study, we relax this assumption and allow workers to choose to remain unemployed or to quit the labor force.

Workers decide against the job offer if the value of non-participation in the labor market is higher than the value of participation (Mortensen 1986). Empirically, we measure the value of non-participation with unemployment benefits. The idea is that the higher the benefits, the higher the value of unemployment. Indeed, empirical findings show that a reduction of unemployment benefit durations leads to shorter periods of unemployment (Card and Levine 2000; Lalive and Zweimueller 2004; van Ours and Vodopivec 2006; Card, Chetty, and Weber 2007; Lalive 2007).

The cut-off, where the value of non-participation equals the value of participation, is the reservation wage. Empirically, we measure the reservation wage with the wage from the previous job. Indeed, the majority of unemployed individuals report reservation wages that are at least as high as the wage they were paid on their last job (Feldstein and Poterba 1984; Neal 1995; Krueger and Mueller 2009, 2016).

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[1] At the extreme, if the probability that the worker is going to remain with his initial firm is very low, he will adopt an investment strategy that is closer to the market weight $\bar{\lambda}$ than to the firm-specific bundle λ_i. Under these circumstances, being laid off is actually good news for the worker. Because he invested in skills that match more closely with the market bundle, switching jobs will allow him to make better use of his skill bundle. The worker might actually realize a wage gain. Similarly, if the market becomes thicker and the number of offers converges to infinity, laid-off workers are certain to find a job that suits their skill bundle. In this case, the wage loss from layoffs is zero. However, these are more theoretical possibilities and not borne out in our data.

[2] The study by Geel, Mure, and Backes-Gellner (2011) focuses on firm-financed training. Using data from the German BIBB/IAB Qualification and Employment Surveys, they construct an index of the skill specificity of different vocational occupations and find support for Lazear's theory.

We apply Lazear's framework to derive the following empirically testable hypotheses: First, the more specific a worker's original occupation, the less likely he will switch occupations. Workers in more specific occupations are less likely to find another occupation that uses a skill combination similar to their own. Second, allowing workers to choose to remain unemployed or to quit the labor force, we derive an additional hypothesis that we can test in Lazear's framework. We expect that the more specific a worker's original occupation, the longer his unemployment spell. This prediction derives from Lazear's modeling of market thickness. Because of the idiosyncratic skill bundles, workers in more specific occupations face a thin market, with a small number of offers. Because they receive only a small number of offers with each draw, these workers are likely to decide to keep searching for a longer period than their counterparts in more general occupations with many draws. Therefore, these workers in more specific occupations should be more likely to remain unemployed for a longer time.

Note that we analyze short-term effects in the sense that we observe labor market outcomes one year after the layoff. While the emphasis in the displacement research has shifted from short-term wage losses to longer-term wage dynamics before and after displacement (Podgursky and Swaim 1987; Jacobson, LaLonde, and Sullivan 1993; Burda and Mertens 2001; Farber 2004; Couch and Placzek 2010), enlarging our analysis of occupational specificity to long-term effects is not feasible for one main reason: Our skills data stems from the year 2004 and we assume that occupational skill requirements do not change over the considered time period, i.e., from 2004 through 2009. However, if we investigate individuals for longer periods of time, this assumption becomes unrealistic. Due to technological and structural changes, skill requirements within occupations might fundamentally change. Moreover, some occupations might become obsolete while other occupations are newly created. Any analysis investigating long-term labor market outcomes has to account for these structural changes. In Switzerland, unfortunately, such skill data is not available.

Moreover, Lazear (2009) predicts that workers at firms with more specific skill combinations have higher wages. He argues that these firms have a lower probability of laying off their workers, because they have more difficulties in replacing them. Consequently, workers are more secure in their current position and they invest more idiosyncratically in the skills that suit their initial firm. However, because of their idiosyncratic investment, these workers also lose more when they are laid off. Translating Lazear's predictions to the level of occupations leads us to our fourth and fifth hypotheses: Workers in more specific occupations earn more but also incur greater wage losses after layoffs than workers in more general occupations.

3.2.2 Skill Distance

Lazear (2009) points out that one motivation for his new view of human capital stems from the empirical fact that the wage losses workers face after layoffs are very heterogeneous. Lazear's model posits the heterogeneity in wage losses is due to firm-specific human capital. Workers in more idiosyncratic firms suffer greater wage losses than workers in more general firms. Therefore, the extent of the wage loss ultimately depends on the proportion of skills that a worker can transfer from one firm to the other.

Transferring Lazear's analysis to the level of occupations, wage losses depend on the proportion of skills that a worker can transfer from one occupation to the other. Recent contributions investigating the transferability of skills introduce the concept of "skill distance" to empirically measure the proportion of skills that are transferable during an occupational change (Poletaev and Robinson 2008; Gathmann and Schoenberg 2010; Robinson 2011). In line with Lazear's model, the underlying hypothesis is that wage changes should be smaller if the original occupation and the new occupation are similar in term of their skills.

These new studies have evolved from the discussions on the source of human capital specificity. While many early studies have estimated the contribution of firm-specific human capital to individual wage growth (Abraham and Farber 1987; Altonji and Shakotko 1987; Kletzer 1989; Topel 1991), more recent evidence suggests that specific human capital might be more tied to an industry (Neal 1995; Parent 2000) or an occupation (Gibbons et al. 2005; Kambourov and Manovskii 2009b) rather than to a particular firm. These studies thus assume that workers lose their human capital if they switch their firm, industry, or occupation. On the contrary, studies calculating the skill distance show that specific human capital is not fully lost if an individual leaves an occupation and therefore argue that specificity is tied to a combination of single skills (Poletaev and Robinson 2008; Gathmann and Schoenberg 2010; Robinson 2011).

These skill distance studies share the same intuition as Lazear (2009) in the sense that they hypothesize that human capital specificity should be measured at the level of skills. However, the skill distance approaches and Lazear's model differ in one crucial point: The skill distance studies assume that all skill bundles are equally general. This assumption means that, empirically, this literature looks at *realized* occupation-to-occupation transitions, compares the underlying skill bundles, and estimates the resulting wage losses.

Lazear's model goes a step further and allows for skill bundles with different degrees of specificity. His model allows accounting for both realized and potential occupation-to-occupation transitions. Depending on their skill bundles, some workers can choose from a large number of job offers while others have a very limited number of offers. The number of job offers, in turn, explains workers' transition patterns. The number of job offers is explicitly modelled in Lazear (2009), while it is absent in the skill distance literature. Lazear explains which workers are more likely to change their occupation, while the skill distance allows estimating the extent of wage change induced by an occupational change. If we combine Lazear's model with the skill distance measure, we can thus provide a thorough explanation for the observed patterns of both occupational mobility and wage changes.

To measure the skill distance between two occupations, we use the Euclidean distance measure. This measure has been used extensively in the network literature to characterize the proximity of race and ethnicity (Conley and Topa 2002), in the innovation literature to characterize the proximity of firms' technologies (Kaiser 2002; Benner and Waldfogel 2008) and recently also in the literature on occupational mobility (Poletaev and Robinson 2008; Robinson 2011). The Euclidean distance between two points in Euclidean space with the coordinates *(x, y)* and *(a, b)* is simply the length of the line segment connecting them. It is given by the formula $\mathrm{dist}\big((\mathrm{x},\mathrm{y})(\mathrm{a},\mathrm{b})\big) = \sqrt{(\mathrm{x}-\mathrm{a})^2 + (\mathrm{y}-\mathrm{b})^2}$.

In our application, this distance measure is particularly valuable for two main reasons. First, it is a straightforward measure and a concept used in many applications.[3] Second, unlike other distance measures, the Euclidean distance is sensitive to the length of the vector, i.e., it takes the number of skills required in the occupation into account (D'Agostino and Dardanoni 2009). We describe two occupations X and Y by their skill bundles X and Y. Then we define the Euclidean distance between occupations X and Y as follows:

$$D_{XY} = \sqrt{\sum_{i=1}^{N} w_i (X_i - Y_i)^2}$$

where the sub-index $i = 1 \ldots N$ indicates the number of skills in the skill bundles and w_i is a weighting factor, which reflects how intensively skills are used in an occupation. In our

[3] For instance, the linear regression model, which is without doubt the workhorse of applied econometrics, relies on the Euclidean distance. Given an n-sized vector y and k n-sized vectors $x_1, \ldots, x_k$, which are collected into an $n \times k$ design matrix X, the linear regression model deals with how to find the point in the linear space spanned by the columns of X which is closest to y. Thus, the problem is to find a k-sized vector β, which minimizes the distance between y and $X\beta$. The most common method for solving this problem is OLS, which implies that Euclidean distance is the chosen distance concept.

application, this weighting factor accounts for the fact that some occupations use up to 12 different skills, while others only use three different skills.

The Euclidean distance measure varies between zero and one. It is zero for occupations that use identical skill sets and one if two occupations use completely different skills sets. In the empirical analysis, we follow previous contributions (Poletaev and Robinson 2008; Robinson 2011) and regress wages in the new occupation on this distance measure. We expect that the larger the skill distance, the larger the wage change.

3.3 Data and Measurements

We use data from Switzerland, a country with a long tradition of dual vocational education and training (VET), where more than half of the workforce holds a VET degree. We use three types of data for our empirical analysis. First, our core data is the Social Protection and Labour Market (SESAM) survey. The SESAM is a survey data set linked with administrative data on employment and unemployment spells. Second, to control for regional and time-specific employment opportunities, we use data on the monthly unemployment rates from the Swiss Federal Statistical Office and match them to the SESAM sample. Third, to construct occupation-specific skill bundles, we use data on skills used in an occupation from the Swiss career-counseling center *Berufsinformationszentrum* (BIZ).

3.3.1 The Social Protection and Labour Market Survey

The Social Protection and Labour Market survey (SESAM) is a matched panel data set linking the Swiss Labour Force Survey (SLFS) with data from different social insurance registers. The SLFS is a representative household panel based on a sample of about 100,000 interviews provided by the Swiss Federal Statistical Office. It provides a rich set of information on employment patterns, socio-demographic, educational, and occupational characteristics. The social insurance registers provide the exact daily duration of individual employment and unemployment spells, as well as monthly earnings and the exact amount of unemployment benefits received. The panel structure allows following individuals over time so that we can observe them before, during, and after the layoff.

The SESAM has at least four advantages over regular household surveys commonly used in the literature studying labor market transitions. First, its administrative nature ensures that we observe the wages associated with each occupation and the exact date of an occupational change. Second, measurement error in wages and occupational titles is much less of a problem than in typical survey data. We are thus able to reduce the bias in our estimates. Third, because the SESAM reports education histories as well as the highest education, we can single out measurement errors in the education variable.[4] Fourth, the SESAM contains a question on the reason of the last job loss, which allows separating those workers who were laid off from those who separated for other reasons. Although one might be concerned that self-reported data on layoffs contains response bias (Bertrand and Mullainathan 2001), previous research has shown that this concern does not apply for our data (Balestra and Backes-Gellner 2017).

We restrict our sample to individuals with a VET degree who are between 18 and 65 years old. To be included in the sample, these individuals have to be laid off at least once during the observation period, and we have to observe them for at least one year after the layoff. Our sample includes both male and female workers. We also include part-time workers since the share of part-time workers in Switzerland is very large. We exclude some individuals who show inconsistencies in their education variable. We also drop all observations with missing values in the dependent or independent variables.

After creating the panel, we are left with a sample of 4,511 observations. The large drop in observations is because unemployment is generally low in Switzerland. Over the observation period, the average unemployment rate is 3.29 percent, varying between 0.7 and 7.6 percent. In addition, only about 13 percent of the unemployed workers have been laid off, whereas the rest are unemployed for reasons such as injuries, quits, retirements, and other.[5]

Table 3.1 provides descriptive statistics. About 60 percent of the sample is male, 48 percent of the individuals are married and about 40 percent are Swiss nationals. Individuals are on average 42 years old and have three years of tenure. Since all these individuals are laid off at some point, average tenure is rather low. Sixty-two percent of the sample is working or has worked fulltime. The average wage is 3,386 Swiss francs and the average unemployment benefits are 917 Swiss francs. Average wages are below the Swiss average (about 5,000 Swiss francs for workers with a VET degree), because all of these individuals experience a layoff during the observation period with zero wages and positive unemployment benefits.

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[4] Comparing the individual education histories with the variable “highest educational attainment” reveals some misclassification in the data. We drop all observations where individuals report VET as their highest educational attainment, but where the individuals’ education histories reveal that they achieved a university degree after the VET degree. Similarly, we keep those observations where individuals report compulsory schooling VET as their highest educational attainment, but where the individuals’ education histories reveal that they have received a VET degree, they work in VET occupations, and have earnings similar to other VET workers in that occupation.

[5] The possible response categories are (in descending order of occurrence in our data): layoff, retirement, sickness/accident, end of fixed-term contract, quit due to bad working conditions, early retirement, end of first job, quit due to being fed up with the job, personal reasons, other reasons, care service, starting education, wish to change job, ceding own business, and mandatory retirement.

Similarly, average unemployment benefits are below the Swiss average, because all of these individuals are in employment at some point during the observation period with positive wages and zero unemployment benefits.[6] We have included an overview of the Swiss unemployment insurance system in Section 3.7 in the Appendix. Applicants who are eligible for unemployment benefits receive 70 percent of their insured wages during an unemployment spell for up to two years. For the average worker with a VET degree, unemployment benefits thus amount to 3,500 Swiss francs per month.

Table 3.1: Descriptive statistics

Variables	Obs.	Mean	St. Dev.	Min	Max
Male	4,511	0.584	0.493	0	1
Married	4,511	0.480	0.500	0	1
Swiss	4,511	0.393	0.488	0	1
Age	4,511	42.28	12.04	17	65
Tenure	4,511	2.900	5.499	0	44
Full-time	4,511	0.591	0.492	0	1
Wage	4,511	3,386	3,822	0	64,200
Unemployment benefits	4,511	917.5	1,912	0	11,050
Firm size	4,511	10.25	4.007	1	14
Industry	4,511	57.23	27.84	0	96
Region	4,511	13.08	8.889	1	26
Local unemployment rate (%)	4,511	3.290	1.316	0.7	7.6
Occupational specificity	4,511	0.275	0.083	0.0353	0.4505
Labor market thickness	4,511	0.064	0.079	0.0001	0.2200
Skill distance	4,511	0.202	0.328	0	1.4142

Notes: SESAM data linked with BIZ data, authors' calculations.

Table 3.2 gives a brief overview of our main outcome variable, the labor market transitions we observe in the SESAM sample. One year after layoff, about 55 percent of all laid-off individuals are reemployed, 18 percent remain unemployed, and 20 percent have left the labor force. Among the reemployed, about 33 percent have changed their occupation. In the analyses of labor market transitions, we use the full sample with 4,511 observations for our investigation. In the analyses of the relationship of specificity and wages, we use the sample of reemployed

[6] The SESAM provides register data on yearly wages and unemployment benefits as well as on the daily employment and unemployment duration. We use this information to compute monthly wages and unemployment benefits. In this way, individuals who were fully employed during a year, will have positive wages and zero unemployment benefits. Viceversa, fully unemployed indivudals will have zero wages and positive unemployment benefits. Because we include these zeros, wages and unemployment benefits in our sample are below the Swiss average.

workers only. Finally, in the analysis of the skill distance, we use the smaller sample of reemployed workers that have switched their occupation.

Table 3.2: Decomposition of labor market transitions

	% of all separations
Total	100
unemployment-to-employment	55.17
of which	
same occupation	67.20
different occupation	32.80
unemployment-to-unemployment	17.68
unemployment-to-out of the labor force	20.36

Notes: SESAM data linked with BIZ data, authors' calculations.

3.3.2 Skill Bundles, Specificity, and Distance

We use data from the career-counseling center *Berufsinformationszentrum* (BIZ) to construct the skill bundles, the specificity measure, and to calculate the skill distance between occupations. The BIZ provides a detailed list of skills that are used in VET occupations. The list comprises 26 different skills and distinguishes between intellectual, personal, and physical skills. Table 3.3 gives an overview of the skills.[7]

Occupational experts, who advise youth on their occupational choice, compile this skill list. Because it is not the workers themselves who report on their skill requirements, the BIZ data might suffer from measurement error. While workers should be very precise in describing their everyday work, it is conceivable that occupational experts over- or underestimate certain skill requirements. This concern is frequently voiced for the O*NET data, the most commonly used data in skill research, which also relies on occupational experts.

While the vast majority of the early job search literature estimates this model structurally, advances in the discrete choice literature have generated much of the econometric methodology needed to estimate the model parametrically (McFadden 1974). In our application, we can thus use the empirical framework of the job search literature and enrich it with Lazear's model. Applying a discrete choice model, we can describe worker's labor market transitions to depend on occupational specificity.

[7] Note that these data are a snapshot. We assume that skill requirements do not change over the considered time period, i.e., from 2004 through 2009.

Although our data does not provide workers' self-assessments, we are confident that measurement error in the BIZ is less of an issue than for the O*NET data. In contrast to O*NET, the state-funded BIZ is the primary source of information for youths' occupational choice. The BIZ cooperates closely with both schools and firms. If the BIZ list were to largely diverge from the actual on-the-job requirements, youths, teachers, and firms would ultimately refrain from using it. Contrarily, the main audience of O*NET are policy makers, who are less closely attached to the actual labor market. Misclassification in the O*NET is therefore less likely to be uncovered. We believe that while workers' self-assessment is the preferable data to work with, due to their constant feedback loop, the BIZ data appear to be very accurate as well.

Table 3.3: Skill categories according to the BIZ

Category	Skills
Intellectual Skills	mental flexibility, abstract-logical thinking, practical understanding, spatial perception, technical understanding, language skills, creativity, sense of aesthetics, organizational skills.
Personal Skills	sense of responsibility, ability to work in a team, openness, communication skills, service mindedness, reliability, psychological stability, patience, perseverance, empathy.
Physical Skills	strong constitution, robust health, manual dexterity, physical mobility, fine motor skills, sense of taste, no fear of heights.

Notes: List provided in German by the Berufsinformationszentrum in Zihlmann et al. (2011); translated by the authors.

In the first step, we construct occupational skill bundles by listing the skills used in an occupation and assigning a weight to each skill depending on the total number of skills used in that occupation. Some occupations such as sales persons use up to 12 different skills, while others such as road builders use only four skills. On average, occupations use seven different skills. To account for this heterogeneity in skill usage, we weight each skill with the number of skills used in an occupation. For example, if an occupation uses four different skills, we attach a weight of 0.25 to each skill, while in an occupation with eight different skills each skill receives a weight of 0.125. Essentially, we describe each occupation by a weighted sum of skills.

In the second step, we construct the market weight as a benchmark for the specificity of the occupational skill bundles. We use the SESAM to construct the market weight, $\bar{\lambda}$.[8] Since the SESAM is a representative survey, it contains the distribution of occupations of the Swiss workforce.[9] For each wave, we know the distribution of the workforce across occupations, and, for each occupation, we know the respective skill bundle. Using both types of information, we rank each of the 26 single skills in the labor market according to their distribution in the labor market. The most general skill occupies the first rank and the most specific skill occupies the twenty-sixth rank. In essence, this ranking constitutes the market weight, $\bar{\lambda}$.[10]

In the third step, we adapt the approach of Geel, Mure, and Backes-Gellner (2011) and determine the degree of occupational specificity by comparing occupational skill bundles with the market weight. This approach allows assigning the degree of occupational specificity to each occupation in our sample. In the final step, we compare the occupational skill bundles of any two occupations to calculate the skill distance between any two occupations.

To better understand our approach, let us walk through an example. Take the occupations of banker and electrician as an example. For simplicity, assume that only these two occupations exist in the labor market. In addition, we limit our example to a four-dimensional skill vector, i.e., the two occupations are characterized by the presence or absence of only four skills.[11] Assume further that a banker has the skills "abstract-logical thinking" and "mathematical skills," and an electrician has the skills "mathematical skills," "fine motor skills," and "spatial thinking."

In the first step, considering these four skills, we describe the skill bundles of the occupations as follows:

banker's skill bundle
$$\lambda_B = \begin{pmatrix} 1 \\ 1 \\ 0 \\ 0 \end{pmatrix} \begin{array}{l} \text{abstract-logical thinking} \\ \text{mathematical skills} \\ \text{fine motor skills} \\ \text{spatial thinking} \end{array}$$

electrician's skill bundle
$$\lambda_E = \begin{pmatrix} 0 \\ 1 \\ 1 \\ 1 \end{pmatrix} \begin{array}{l} \text{abstract-logical thinking} \\ \text{mathematical skills} \\ \text{fine motor skills} \\ \text{spatial thinking} \end{array}$$

[8] As the SESAM uses the same occupational categories as the BIZ, we can easily match the information from our occupation-specific skill bundles. The occupational code available in both data is the *Schweizer Berufs-nomenklatur 2000* (SBN2000), a five-digit code.
[9] In the Appendix in Section A.3.7.1, we provide a list of vocational occupations that are included in our sample.
[10] To account for changes in skill demand over time, we calculate the market bundles separately for each wave.
[11] In the actual data we have 26-dimensional skill vectors.

In the second step, we construct the market weight. The market weight in our example is a four-dimensional skill vector that contains a rank order of our four skills. The rank order is determined by the distribution of skills in the labor market. Suppose that the market comprises 500 bankers and 300 electricians. Looking at the underlying skill bundles, we see that 500 workers use the skill "abstract-logical thinking," 800 workers use the skill "mathematical skills," and 300 workers use the skills "fine motor skills" and "spatial thinking." Thus, in our labor market with only bankers and electricians, the market weight $\bar{\lambda}$ is defined as:

market weight $$\bar{\lambda} = \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix} \cdot \begin{pmatrix} 500 \\ 800 \\ 300 \\ 300 \end{pmatrix} \begin{matrix} \text{abstract-logical thinking} \\ \text{mathematical skills} \\ \text{fine motor skills} \\ \text{spatial thinking} \end{matrix}$$

This leads to the following ranked order of skills: Mathematical skills are the most general skills because they are most widely used. The skill "abstract-logical thinking" is the second most general skill, because 500 workers use it. The skills "fine motor skills" and "spatial thinking" are the least general skills, because only 300 workers use it.

In the third step, we derive the specificity measure for the occupation-specific skill bundles by dividing the sum of ranks by the sum of skills used in an occupation. The bank clerk uses two skills and therefore we assign the value 0.5 to each of his skills. The electrician uses three skills and therefore we assign the value $0.\overline{3}$ to each of his skills. Formally, occupational specificity is defined as:

specificity measure occupation j

$$S_j = \frac{\sum_{i=1}^{n} m_i}{\sum_{i=1}^{n} n_i} = \frac{sum\ of\ ranks}{sum\ of\ skills}$$

Turning to our example, the banker's specificity is:

specificity measure banker

$$S_b = \frac{sum\ of\ ranks}{sum\ of\ skills} = \frac{2+1+0+0}{2} = 1.5$$

The electrician's specificity is:

specificity measure electrician

$$S_e = \frac{sum\ of\ ranks}{sum\ of\ skills} = \frac{0+1+3+3}{3} = 2.\overline{3}$$

According to our specificity measure, the electrician is a more specific occupation than the banker. Applying this procedure to the whole set of occupations in the labor market, we develop a continuous measure of occupational specificity.

In the final step, we calculate the skill distance between occupations by applying the Euclidean distance formula. Turning to our example of bankers and electricians, the Euclidean distance between those two occupations is given by:

$$D_{XY} = \sqrt{\begin{pmatrix} 0.5 & & 0 \\ 0.5 & - & 0.3 \\ 0 & & 0.3 \\ 0 & & 0.3 \end{pmatrix}^2} = \sqrt{0.5^2 + 0.2^2 + (-0.3)^2 + (-0.3)^2} = 0.685.$$

In our example, the distance between bankers and electricians is 0.685. Judging whether this distance is large or small is of course only possible by comparing this distance to distances between other occupations.

3.4 Empirical Approach

We proceed in three steps to test our hypotheses. First, to analyze whether occupational specificity influences the likelihood of different types of labor market transitions, we estimate a multinomial logit model. Second, to explore how occupational specificity affects wages, we run two separate regressions. To investigate whether more specific occupations pay a wage premium, we use Poisson pseudo-maximum likelihood estimation (PPML) with wages in the original occupation as dependent variables. Then, to investigate changes in wages we use OLS estimation with the difference in log wages as dependent variable. Third, to analyze whether the skill distance between occupations is associated with wage changes, again, we use PPML and include a measure for skill distance in our regression.

Before running the regressions, we standardize the variables occupational specificity, labor market thickness, and skill distance to have a mean of zero and a standard deviation of one. This procedure simplifies the interpretation of the effects. For the standardized variables, each case's value indicates its difference from the mean of the original variable in number of standard deviations. For example, a value of 0.5 indicates that the value for that case is half a standard deviation above the mean, while a value of -2 indicates that a case has a value two standard deviations lower than the mean.

3.4.1 Occupational Specificity and Labor Market Transitions

We distinguish between four different types of labor market transitions for laid-off individuals: finding employment in the original occupation, finding employment in a different occupation, remaining unemployed, or quitting the labor force. We estimate the probability of these transitions as a function of an individual's occupational specificity. Our empirical approach follows the set-up in Lazear's skill-weights-approach.

Lazear's model is embedded in the traditional job search models (Mortensen 1986; Mortensen and Pissarides 1999) in the sense that his model allows for an exogenous probability of layoff, and that the length of time a workers spends unemployed and the wage received once re-employed are both random variables with distributions that depend on the worker's characteristics and those of the environment. Specifically, traditional models assume that an unemployed worker compares the present value of different labor market outcomes and chooses the outcome with the highest utility.

The theoretical framework of McFadden's discrete choice model can be described as follows: The individual i assigns utility to alternative j and selects the alternative with the highest utility (McFadden 1974). The probability of each type of transition j depends on a vector of observed characteristics, X_i. Mathematically, a worker's choice can be expressed as follows:

$$\pi_j(\mathrm{x}_{it}; \beta) = \frac{\exp(x_{it}'\beta_j)}{1 + \sum_{r=2}^{J} \exp(x_{it}'\beta_r)} \tag{3.1}$$

$$with\ \ x_{it}'\beta = \beta_0 + \beta_1 \cdot OS_{it} + c_{it}'\beta_2 + \beta_3 \cdot UR_{it} + \beta_4 \cdot LMT_{it} + \varphi + \delta.$$

In our baseline model, our dependent variables are a set of four dummy variables indicating labor market status one year after the layoff: employed in the same occupation as before the layoff, employed in a different occupation, unemployed, and out of the labor force. For identification purposes we choose the most frequent outcome—"reemployed in the original occupation"—as the reference category.

Throughout this chapter, we use the following concepts and definitions: A layoff in time t is defined as a situation where the person is employed at a firm in time $t-1$ but not employed in time t, and reports in time t that he has been laid off. Concerning labor market transitions, an occupational change occurs if the person is unemployed in time t, reemployed in time $t+1$ and holds a different occupation in $t+1$ than he did in $t-1$, before becoming unemployed. In contrast, the person is reemployed in the same occupation if the occupation held in $t-1$

corresponds to the occupation held in $t + 1$. A person continues being unemployed f he is registered as unemployed in both t and $t + 1$. Finally, a person has left the labor force, if he is unemployed in t, and neither employed nor registered as unemployed in $t + 1$.

The observed characteristics x_{it} comprise the following variables. First, OS_{it} is our main variable of interest, occupational specificity. Second, c'_{it} comprises a set of control variables, used in the traditional job search models (Mortensen 1986; Mortensen and Pissarides 1999). The included controls for the individual characteristics are age and age squared (in years), tenure and tenure squared (in years), a part-time dummy, and gender and nationality dummies. In addition, we include firm size (five categories), and industry (18 categories) as firm characteristics. Third, to control for labor market conditions, we include UR_{it}, the local unemployment rate, and LMT_{it}, the labor market thickness on the occupation level. Finally, φ are time dummies, and δ are region dummies.

In the first specification, we also include the natural logarithm of wages in the original occupation and the natural logarithm of unemployment benefits to control for the value of the reservation wage and the outside option. Concerning the timing of these variables, as pre-layoff wage we include wages in the last job hold before the layoff, while unemployment benefits are measured in the year of the layoff.

However, because wage and unemployment benefits may be endogenous, these coefficients should be interpreted with caution (Abowd and Kang 2002). Because wages and benefits are an outcome of occupational specificity, including these controls might bias the coefficient on occupational specificity.[12] Therefore, we use a second specification where we do not control for wages and unemployment benefits.

[12] The amount of unemployment benefits is tied to previous earnings.

3.4.2 Occupational Specificity and Wages

To assess the effect of occupational specificity on wages, we estimate two separate wage regressions. In the first regression, we use Poisson pseudo-maximum likelihood (PPML) estimation, where the parameters of interest solve the condition:

$$\sum_{i=1}^{n}[y_{it} - \exp(x_{it}'\beta)] \cdot x_{it} = 0, \tag{3.2}$$

$$with\ x_{it}'\beta = \beta_0 + \beta_1 \cdot OS_{it-1} + \beta_1 \cdot y_{it-1} + c_{it}'\beta_2 + \beta_3 \cdot UR_{it} + \beta_4 \cdot LMT_{it} + \varphi + \delta,$$

where y_{it-1} is the monthly wage in the original occupation, OS_{it-1} is the specificity in the original occupation, and c_{it} is the vector of controls we have included previously. In addition, we control for the local unemployment rate and the labor market thickness. Finally, φ are time dummies, and δ are region dummies.

Estimating this model with PPML is preferred over OLS estimation for two main reasons. First, with heteroskedastic errors, PPML is the least biased estimator out of a various number of OLS functional forms such as non-linear least squares or Tobit models. Second, PPML allows for predictions on wage levels instead of log wages as in the case for OLS (Santos Silva and Tenreyro 2006, 2011). In the second regression, we condition on those workers who are reemployed and define y_{it} as the difference in log wages before and after the layoff.

3.4.3 Skill Distance and Wages

To analyze whether the skill distance is associated with changes in wages, we condition on reemployed individuals and use PPML to estimate parameters that solve the equation:

$$\sum_{i=1}^{n}[y_{it} - \exp(x_{it}'\beta)] \cdot x_{it} = 0 \tag{3.3}$$

$$with\ \ x_{it}'\beta = \beta_0 + \beta_1 y_{it-1} + \beta_2 distance_{it} + c_{it}'\beta_3 + \beta_4\ UR_{it} + \beta_5 LMT_{it} + \varphi + \delta,$$

where y_{it} is the monthly wage in the new occupation, y_{it-1} is the wage in the original occupation, and $distance_{it}$ is the skill distance measure. Again, we include all controls from the previous equations.

3.5 Results

In this section, we present our estimation results. First, we show the results of the multinomial logit estimation where we test whether occupational specificity has an effect on the likelihood of different types of labor market transitions. Second, we show the results from the estimations where we investigate the relationship between occupational specificity and wages as well as skill distance and wages.

3.5.1 Occupational Specificity and Labor Market Transitions

Tables 3.4 through 3.6 report the estimation results of the multinomial logit model, where we test our first two hypotheses.[13] First, we show how occupational specificity affects the log-odds ratios of the alternative outcomes compared to the baseline outcome "being reemployed in the same occupation." Second, we calculate the marginal effects to show how occupational specificity affects the probability of each possible labor market transition. The parameters of the multinomial logit model are not straightforward to interpret. Looking at the log-odds ratios, a positive parameter means that the probability of choosing *j* increases relative to the probability of the base outcome. However, the magnitude of the parameter has no direct intuitive meaning.

In Table 3.4 column (1), the coefficient of interest, "occupational specificity," is negative and statistically significant at the five percent level. This implies that the log-odds ratio of finding reemployment in a different occupation compared to reemployment in the original occupation is decreasing in occupational specificity. This result confirms our hypothesis. The higher the degree of specificity of a worker's initial occupation, the less likely he will switch to a different occupation.

Column (2) shows the estimates for how occupational specificity affects the probability of remaining unemployed one year after the layoff versus having found reemployment in the same occupation. Occupational specificity increases the log odds ratio of still being unemployed versus having found reemployment in the same occupation. The effect is statistically significant at the one percent level. Again, we confirm our hypothesis that the higher the degree of specificity of a worker's original occupation, the more likely he will remain unemployed in the period following the layoff.

[13] In an alternative specification, reported in the Appendix in Tables A.3.1 and A.3.2, we cluster the standard errors at the occupational level. It is reasonable to expect that the error terms for workers in the same occupation are not independent. However, clustering does not change the results qualitatively.

Column (3) shows that occupational specificity does not affect the log odds ratios of dropping out of the labor force versus having found reemployment in the same occupation. The decision to leave the labor force appears to be driven by age and tenure effects as well as socio-demographic variables instead of the specificity of a worker's occupation.

Among the control variables, labor market thickness—as expected—decreases the likelihood of changing the occupation and decreases the likelihood of remaining unemployed versus finding employment in the same occupation. This finding is straightforward: The more job offers a laid-off individual has, i.e., the higher the labor market thickness, the more likely he will find employment in the occupation he is trained in. The unemployment rate has a marginally statistically significant negative effect of leaving the labor force. This might be because unemployment is overall rather low in Switzerland.

Unemployment benefits increase the probability of changing occupation and of remaining unemployed and they decrease the probability of leaving the labor force. Wages earned in the original occupation decrease the likelihood of choosing any other outcome than being reemployed in the same occupation. Given that these variables are proxies for the outside option and the reservation wage, the signs of these coefficients are in line with expectations.

However, as pointed out previously, wages and benefits are to some extent outcomes of occupational specificity, which might bias the specificity coefficient. In Table 3.5, we therefore repeat the multinomial logit regression without controlling for wages and unemployment benefits. We find the coefficients of interest to be unaffected by whether we control for wages or benefits or not. They change neither in direction nor in levels of statistical significance.

In the next step, to interpret the effects of occupational specificity on the probability scale, we need to compute marginal effects. The marginal effects inform us about the likelihood of the four outcomes independent from the base outcome. Table 3.6 reports marginal effects of a one standard deviation increase in occupational specificity on all four outcomes considered in our analysis based on the estimates from Table 3.5.

Our results indicate that for a worker i with mean characteristics $\bar{x}_i$, an increase in occupational specificity by one standard deviation increases the probability of reemployment in the original occupation by 0.13 percentage points. Again, this is in line with Lazear's predictions. The more specific the skill bundle, the more likely is reemployment in the original occupation. In the same vein, the probability of being reemployed in a different occupation decreases by 2.99 percentage points if occupational specificity increases by one standard deviation. The more specific the skill bundle, the less likely is an occupational change. In line with expectations, the probability of remaining unemployed increases by 4.01 percentage points if occupational specificity increases by one standard deviation. The probability of having left the labor force is not influenced by occupational specificity.

Looking at the average probabilities, i.e., the probability of choosing one of the alternatives *j* for all individuals in the sample, our results suggest that workers in more specific occupation are most likely to find reemployment in their original occupation, second most likely to remain unemployed for a longer time span, and finally the least likely to switch occupations.

Table 3.4: MNL regression: Occupational specificity and employment status, controlling for income

	occupational change	*unemployed*	*out of the labor force*
Occupational specificity	-0.2637**	0.3862***	-0.1172
	(0.1241)	(0.1431)	(0.2717)
Labor market thickness	-0.3178**	-0.1660	-0.1173
	(0.1399)	(0.1505)	(0.2792)
Unemployment rate	-0.1637	0.7923	-1.4574
	(0.4692)	(0.5257)	(1.0292)
Unemployment benefits	0.0778***	0.3035***	-0.3617***
	(0.0268)	(0.0294)	(0.0952)
Wage	-0.0358	-0.3825***	-0.6303***
	(0.0389)	(0.0351)	(0.0568)
Age	-0.0858	-0.0295	-0.2457**
	(0.0556)	(0.0699)	(0.1046)
Age squared	0.0009	0.0003	0.0038***
	(0.0007)	(0.0008)	(0.0012)
Tenure	-0.1770**	0.3493***	-0.8655***
	(0.0837)	(0.0710)	(0.1506)
Tenure squared	0.0071*	-0.0069*	0.0271***
	(0.0037)	(0.0036)	(0.0051)
Swiss	0.2591	-0.3912*	0.0116
	(0.1884)	(0.2303)	(0.3974)
Male	0.2181	-0.0992	0.9205**
	(0.1852)	(0.2109)	(0.3806)
Married	-0.1430	0.4273*	-2.7106***
	(0.1881)	(0.2223)	(0.4559)
Full-time	-0.0300	-1.8795***	3.8435***
	(0.1875)	(0.2225)	(0.5662)
Firm size	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Region	Yes	Yes	Yes
Year	Yes	Yes	Yes
Pseudo R squared	0.5185	0.5185	0.5185
Observations	1,653	1,653	1,653

Notes: SESAM data linked with BIZ data, authors' calculations.
Multinomial Logit regression (standard errors in parentheses).
The base outcome is being reemployed in the same occupation.
Significance levels: * < 0.1; ** < 0.05; *** < 0.01.

Table 3.5: MNL regression: Occupational specificity and employment status

	occupational change	*unemployed*	*out of the labor force*
Occupational specificity	-0.2570**	0.3547***	-0.2350
	(0.1220)	(0.1232)	(0.1838)
Labor market thickness	-0.3032**	-0.1447	-0.0146
	(0.1375)	(0.1271)	(0.1883)
Unemployment rate	-0.1510	0.8669**	-0.4672
	(0.4615)	(0.4338)	(0.6188)
Age	-0.0783	-0.0559	-0.3477***
	(0.0548)	(0.0593)	(0.0741)
Age squared	0.0008	0.0008	0.0050***
	(0.0007)	(0.0007)	(0.0008)
Tenure	-0.2040**	0.3352***	-1.4246***
	(0.0821)	(0.0652)	(0.1690)
Tenure squared	0.0085**	-0.0041	0.0433***
	(0.0037)	(0.0035)	(0.0052)
Swiss	0.1661	-0.5244***	-0.0442
	(0.1847)	(0.1951)	(0.2589)
Male	0.2030	-0.1383	1.2161***
	(0.1823)	(0.1809)	(0.2620)
Married	-0.1861	0.4171**	-2.3926***
	(0.1852)	(0.1900)	(0.2962)
Full-time	-0.0140	-2.0168***	4.0113***
	(0.1837)	(0.1928)	(0.4944)
Firm size	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Region	Yes	Yes	Yes
Year	Yes	Yes	Yes
Pseudo R squared	0.3928	0.3928	0.3928
Observations	1,653	1,653	1,653

Notes: SESAM data linked with BIZ data, authors' calculations.
Multinomial Logit regression (standard errors in parentheses).
The base outcome is being reemployed in the same occupation.
Significance levels: * < 0.1; ** < 0.05; *** < 0.01.

Table 3.6: Marginal effects of a change in occupational specificity

Variables	same occupation	occupational change	unemployed	out of the labor force
Occupational Specificity	0.0013 (0.0161)	-0.0299** (0.0119)	0.0401*** (0.0114)	-0.0115 (0.0098)
Average probability	0.4721	0.1339	0.2489	0.1451

Notes: SESAM data linked with BIZ data, authors' calculations.
Marginal effects of a one standard deviation change in occupational specificity on the 4 outcome probabilities.
Standard errors in parentheses.
Significance levels: * < 0.1; ** < 0.05; *** < 0.01.

3.5.2 Occupational Specificity and Wages

Table 3.7 column (1) reports estimates from a wage regression that uses the Poisson pseudo-maximum likelihood (PPML) method. In line with Lazear's predictions, we find a positive correlation between the degree of specificity and wages. Workers receive a wage premium of about 11.1 percent for employment in a one standard deviation more specific occupation. Thus, we confirm our hypothesis that higher specificity is associated with higher wages. Among the control variables, the coefficients are in line with expectations. Labor market thickness has a statistically significant negative effect on wages. If thickness of the market increases, skill bundles become more general and the wage premiums decrease. Age and tenure have the expected U-shaped and inverse U-shaped effects.

In the next step, we test the hypothesis of whether workers in more specific occupations lose more when they suffer a layoff. Table 3.7 column (2) reports estimates from an OLS regression that uses the change in wages before and after the layoff as dependent variable. Here, we restrict our sample to those workers who have found reemployment one year after the layoff. In line with Lazear's model, we find a negative correlation between the degree of specificity and wage changes. Specifically, workers lose about 13.5 percent of their wages for employment in a one standard deviation more specific occupation. We thus confirm our hypotheses. Taken together, these results suggest a risk-return trade-off in the sense that investments into more specific human capital are associated with higher returns but also with higher risk of unemployment and greater wage loss after layoffs.

Table 3.7: Occupational specificity and wages

	monthly wage	*wage changes*
Occupational specificity	0.1106***	-0.1352*
	(0.0223)	(0.0744)
Labor market thickness	-0.0635**	0.0396
	(0.0264)	(0.0769)
Unemployment rate	-0.0490	-0.2867
	(0.0773)	(0.2481)
Age	0.1123***	0.0876**
	(0.0120)	(0.0396)
Age squared	-0.0015***	-0.0012**
	(0.0001)	(0.0005)
Tenure	-0.0068	-0.0009
	(0.0079)	(0.0334)
Tenure squared	0.0006*	0.0007
	(0.0003)	(0.0015)
Swiss	0.2185***	-0.0749
	(0.0337)	(0.1027)
Male	-0.0582*	-0.2092*
	(0.0330)	(0.1182)
Married	0.5051***	0.0720
	(0.0379)	(0.1193)
Full-time	0.2454***	0.0524
	(0.0357)	(0.1298)
Firm size	Yes	Yes
Industry	Yes	Yes
Region	Yes	Yes
Year	Yes	Yes
Method	Poisson	OLS
(Pseudo) R squared	0.2232	0.0826
Observations	4,511	1,008

Notes: SESAM data linked with BIZ data, authors' calculations.
Robust standard errors in parentheses.
Significance levels: * < 0.1; ** < 0.05; *** < 0.01.

3.5.3 Skill Distance and Wages

We investigate the relationship between wages and skill distance by again using Poisson pseudo-maximum likelihood (PPML) estimation. Table 3.8 shows how pre-layoff wages are correlated with post-layoff wages among those who found reemployment in our sample, and how the skill distance between pre- and post-layoff occupation drives this relationship.

We regress post-layoff wages on pre-layoff wages and on skill distance. Specification (1) regresses post-layoff wages on pre-layoff wages without accounting for the skill distance. The correlation is positive and statistically significant. The coefficient on pre-layoff wages indicates how post-layoff wages change in percent if pre-layoff wages increase, ceteris paribus, by 1,000 Swiss francs. One thousand Swiss francs higher monthly wages before the layoff translate into about 0.004 percent higher monthly wages in the new job.

In specification (2) we include the skill distance between the pre-layoff and the post-layoff occupations into our regression. The coefficient shows how post-layoff wages change with skill distance. For an increase of a one standard deviation in skill distance, post-layoff wages decrease by about 3.18 percent. The results in Table 3.8 thus confirm our hypothesis and show that the larger the skill distance, the greater the associated wage losses. Put differently, because they can transfer a large part of their skill bundle from the original to the new occupation, staying close to the skill bundle of the original occupation benefits workers.

Table 3.8: Skill distance and wages

	Wage post layoff	*Wage post layoff*
Pre-layoff wage	0.00004*** (0.00001)	0.00004*** (0.00001)
Skill distance		-0.0318* (0.0193)
Labor market thickness	0.0266 (0.0212)	0.0217 (0.0212)
Unemployment rate	-0.0912 (0.1056)	-0.0963 (0.1058)
Age	0.0335* (0.0179)	0.0332* (0.0179)
Age squared	-0.0004** (0.0002)	-0.0004** (0.0002)
Tenure	-0.0600** (0.0288)	-0.0591** (0.0289)
Tenure squared	-0.0005 (0.0018)	-0.0004 (0.0018)
Swiss	0.1474*** (0.0455)	0.1419*** (0.0455)
Male	0.0493 (0.0454)	0.0490 (0.0453)
Married	0.2495*** (0.0498)	0.2466*** (0.0497)
Full-time	0.4494*** (0.0578)	0.4461*** (0.0577)
Firm size	Yes	Yes
Industry	Yes	Yes
Region	Yes	Yes
Year	Yes	Yes
Method	Poisson	Poisson
Pseudo R squared	0.4281	0.4295
Observations	1,008	1,008

Notes: SESAM data linked with BIZ data, authors' calculations.
Robust standard errors in parentheses.
Significance levels: * < 0.1; ** < 0.05; *** < 0.01.

3.6 Conclusion

This chapter analyzes returns to educational investments from the individual perspective. In particular, we investigate how different types of VET occupations differ in their degree of specificity and how these differences affect workers' mobility and wages. We use Lazear's skill-weights approach (2009) to define the specificity of VET occupations. Lazear assumes that all skills are general in nature but that firms use single skills in different combinations and with different weights. Drawing on this approach, we characterize VET occupations by skill bundles and build occupation-specific skill weights to measure the degree of specificity. We then derive empirically testable hypotheses on the effect of occupational specificity on mobility and wages of VET graduates.

Instead of moving voluntarily because of a better work opportunity, workers might be forced to move because their firm shuts down or they are laid off. In this chapter, we focus on involuntary moves and study the impact of occupational specificity on labor market transitions of laid-off workers. In line with Lazear's predictions, we find that workers in more specific occupations are less likely to find reemployment in a different occupation than their original occupations. Moreover, the more specific their occupation, the more likely they stay unemployed one year after the layoff.

Relating occupational specificity to wages, Lazear (2009) argues that workers have higher wages and suffer larger wage losses in firms that require unusual skill combinations. Translating Lazear's predictions to the occupational level, we derive the following empirically testable hypotheses: Workers in more specific occupations have higher wages and suffer larger wage losses than workers in more general occupations. In our empirical analysis, we confirm these hypotheses. We find that while occupational specificity is associated with higher wages, it is also associated with higher wage losses after layoff.

Finally, we investigate the transferability of skills in more detail. We calculate the skill distance between occupations, which indicates how similar the original and the new occupation are in terms of their underlying skill bundles. We find that the larger the skill distance between two occupations, the higher the wage losses for workers who change between these occupations. Taken together, these findings suggest a risk-return trade-off in the sense that workers in more specific occupations are compensated for their lower mobility with higher wages.

Our analyses of breaking down occupations into skill bundles and classifying occupations in terms of their specificity helps to better understand labor market transitions and wages. We show that it is not the occupation per se but rather the compatibility of the skill bundle of an occupation in comparison to the market weight and in comparison to the skill bundle of other occupations that matters for labor market success.

Because occupational skills of workers are important both for individual returns to education and the competitiveness of firms, the next chapter continues investigating the relation between skill bundles and wages. Due to continuous technological innovation, skill requirements not only increase rapidly but also change frequently (Autor and Dorn 2009). As structural change challenges traditional occupational demarcations, mobility and flexibility are increasingly demanded from both the firm and the individual. The next chapter takes a dynamic perspective on occupational skills and investigates how the demand for and supply of single skills has changed over a period of three decades and how these changes interact with changes in the wage distribution.

3.7 Appendix

Unemployment insurance in Switzerland

The State Secretariat for Economic Affairs (SECO) administers the unemployment insurance in Switzerland. Contributions to the unemployment insurance are equal to 2.2 percent of the monthly gross wages up to 10,500 Swiss francs (126,000 CHF per year). Employers and employees pay equal shares of this insurance premium, i.e., each one contributes 1.1 percent. Additionally, one percent of monthly gross wages beyond 10,500 Swiss francs has to be paid as a "solidarity supplement." These contributions are mandatory for all employees in Switzerland. Self-employed workers can join the unemployment insurance on a voluntary basis.

To be eligible for unemployment benefits, applicants must fulfill a number of conditions. Spells must be longer than two days to be considered as unemployment. Unemployed individuals must live in Switzerland and must apply for benefits at the local registration office. There they will be assigned a case worker, who can impose benefit sanctions if they fail to apply for jobs (Arni, Lalive, and van Ours 2013). The applicants must have contributed during at least 12 months over the preceding two years. If they are eligible, unemployed individuals receive 70 percent of their insured wages (at a maximum of 70 percent of 10,500 CHF) during an unemployment spell of up to two years. Under certain circumstances (obligation to provide for children, disability), this rate can increase from 70 to 80 percent.

Table A.3.1: MNL regression: Occupational specificity and labor market transitions, controlling for income and with clustered standard errors

	occupational change	*unemployed*	*out of the labor force*
Occupational specificity	-0.2729*	0.4087**	0.1316
	(0.1545)	(0.1808)	(0.2976)
Labor market thickness	-0.3069	-0.1898	-0.2652
	(0.2260)	(0.1700)	(0.2407)
Unemployment rate	-0.1774	1.0249**	-1.9660*
	(0.5335)	(0.4102)	(1.0068)
Unemployment benefits	0.0922***	0.3014***	-0.3236***
	(0.0263)	(0.0295)	(0.0904)
Wage	-0.0185	-0.3710***	-0.6599***
	(0.0323)	(0.0371)	(0.0700)
Age	-0.1035**	-0.0372	-0.3421***
	(0.0501)	(0.0963)	(0.1072)
Age squared	0.0010*	0.0003	0.0048***
	(0.0006)	(0.0011)	(0.0012)
Tenure	-0.1243	0.3425***	-0.7884***
	(0.1009)	(0.0907)	(0.1744)
Tenure squared	0.0053	-0.0071	0.0246***
	(0.0042)	(0.0045)	(0.0059)
Swiss	0.2912*	-0.3956*	0.2251
	(0.1656)	(0.2093)	(0.2563)
Male	0.2103	-0.1301	1.2185***
	(0.1638)	(0.1969)	(0.3235)
Married	-0.1321	0.4870**	-2.9247***
	(0.1813)	(0.2242)	(0.4477)
Full-time	-0.1114	-1.9892***	3.7344***
	(0.1964)	(0.4132)	(0.8436)
Firm size	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Region	Yes	Yes	Yes
Year	Yes	Yes	Yes
Pseudo R squared	0.5200	0.5200	0.5200
Observations	1,518	1,518	1,518

Notes: SESAM data linked with BIZ data, authors' calculations.
Multinomial Logit regression (clustered standard errors in parentheses).
The base outcome is being reemployed in the same occupation.
Significance levels: * < 0.1; ** < 0.05; *** < 0.01.

Table A.3.2: MNL regression: Occupational specificity and labor market transitions, with clustered standard errors

	occupational change	*unemployed*	*out of the labor force*
Occupational specificity	-0.2574*	0.3995***	0.0355
	(0.1559)	(0.1471)	(0.2257)
Labor market thickness	-0.2979	-0.2025	-0.1863
	(0.2255)	(0.1364)	(0.1783)
Unemployment rate	-0.1305	1.0932***	-0.5538
	(0.5306)	(0.3525)	(0.5653)
Age	-0.0926*	-0.0624	-0.4254***
	(0.0486)	(0.0740)	(0.0840)
Age squared	0.0010*	0.0009	0.0059***
	(0.0006)	(0.0009)	(0.0009)
Tenure	-0.1673	0.3112***	-1.2761***
	(0.1108)	(0.0973)	(0.2228)
Tenure squared	0.0077	-0.0030	0.0404***
	(0.0066)	(0.0060)	(0.0066)
Swiss	0.1860	-0.5498***	0.0406
	(0.1624)	(0.1873)	(0.2390)
Male	0.1788	-0.2165	1.4617***
	(0.1596)	(0.1925)	(0.2656)
Married	-0.1850	0.4316*	-2.4637***
	(0.1817)	(0.2296)	(0.3219)
Full-time	-0.0947	-2.1421***	3.8655***
	(0.1928)	(0.3621)	(0.7384)
Firm size	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Region	Yes	Yes	Yes
Year	Yes	Yes	Yes
Pseudo R squared	0.3940	0.3940	0.3940
Observations	1,518	1,518	1,518

Notes: SESAM data linked with BIZ data, authors' calculations.
Multinomial Logit regression (clustered standard errors in parentheses).
The base outcome is being reemployed in the same occupation.
Significance levels: * < 0.1; ** < 0.05; *** < 0.01.

Table A.3.3: Vocational occupations in Switzerland

Title of occupation	German title of occupation
Farmer	Landwirt
Winemakers	Winzer
Horticulturist	Gemüsegärtner
Groom	Pferdefachmann
Poultry specialist	Geflügelfachmann
Animal keeper	Tierpfleger
Gardener	Gärtner
Florist	Florist
Forester	Forstwart
Dairy technologist	Milchtechnologe
Butcher	Fleischfachmann
Baker-Confectioner	Bäcker-Konditor
Miller	Müller
Food technologist	Lebensmitteltechnologe
Wine technologist	Weintechnologe
Textile designer	Textilgestalter Handweben
Clothes designer	Bekleidungsgestalter
Orthopaedic shoemaker	Orthopädie-Schuhmacher
Saddler	Sattler
Precision optician	Feinwerkoptiker
Ceramic modeller	Keramik-Modelleur
Casting technologist	Gusstechnologe
Galvanizer	Galvaniker
Production mechanic	Mechapraktiker
Engraver	Graveur
Plant manufacturer	Anlagen- und Apparatebauer
Blacksmith	Schmied
Metal worker	Metallbauer
Automotive technician	Fahrzeugschlosser
Metal spinner	Metalldrücker
Metalworker	Mechapraktiker
Mechanical engineer	Polymechaniker
Textile mechanic	Textilmechaniker
Multimedia technician	Multimediaelektroniker
Power line technician	Netzelektriker
Automation engineer	Automatiker
Electronics technician	Elektroniker
Watchmaker (practitioner)	Uhrmacher Praktiker
Surface finisher	Oberflächenveredler Uhren
Panel beater	Carrossier Spenglerei
Motor mechanic	Automobil-Mechatroniker

Notes: List provided by the Berufsinformationszentrum and matched with SESAM. Authors' translation.

Table A.3.3: Vocational occupations in Switzerland (continued)

Title of occupation	German title of occupation
Agricultural machinery mechanic	Landmaschinenmechaniker
Painter and varnisher	Carrossier Lackiererei
Sawyer	Säger Holzindustrie
Wood turner	Drechsler
Cabinetmaker	Schreiner
Basket worker	Korb- und Flechtwerkgestalter
Gilder	Vergolder
Paper technologist	Papiertechnologe
Polygraph	Polygraf
Screen printer	Siebdrucker
Print media processor	Printmedienverarbeiter
Laboratory assistant	Laborant
Photo lab technician	Fotolaborant
Plastics technologist	Kunststofftechnologe
Model maker	Technischer Modellbauer
Surveyor	Geomatiker
Electrical designer	Elektroplaner
Textile technologist	Textiltechnologe
Telematics technician	Telematiker
IT technician (system technology)	Informatiker (Systemtechnik)
Draughtsman (architecture)	Hochbauzeichner
Draughtsman (spatial planning)	Raumplanungszeichner
Draughtsman (structures)	Bauzeichner
Metal construction engineer	Metallbaukonstrukteur
Building services planners	Haustechnikplaner
Interior designer	Innenausbauzeichner
Micro designer	Mikrozeichner
Constructing engineer	Konstrukteur
Woodworker	Holzhandwerker
Plant operator	Anlagenführer
IT technician	Informatiker
Mediamatician	Mediamatiker
IT technician (support)	Informatiker (Support)
Bricklayer	Maurer
Carpenter	Zimmermann
Road builder	Strassenbauer
Paver	Pflästerer
Foundation engineer	Grundbauer
Floor layer	Bodenleger
Roofer	Dachdecker
Plasterer	Gipser

Notes: List provided by the Berufsinformationszentrum and matched with SESAM.
Authors' translation.

Table A.3.3: Vocational occupations in Switzerland (continued)

Title of occupation	German title of occupation
Painter	Maler
Foundation engineer	Grundbauer
Floor layer	Bodenleger
Roofer	Dachdecker
Foundation engineer	Grundbauer
Floor layer	Bodenleger
Roofer	Dachdecker
Plasterer	Gipser
Painter	Maler
Installer for heating systems	Heizungsinstallateur
Tinsmith	Spengler
Insulation installer	Isolierspengler
Stove builder	Hafner
Glazier	Glaser
Electrician	Elektroinstallateur
Plumber	Sanitärinstallateur
Sunshades fitter	Storenmonteur
Stonemason	Steinmetz
Retail clerk	Detailhandelsfachmann
Bookseller	Buchhändler
Druggist	Drogist
Commercial employee	Kaufmann
Advertising engineer	Gestalter Werbetechnik
Railway operations manager	Bahnbetriebsdisponent
Track worker	Gleisbauer
Train conductor	Zugbegleiter
Cableway technician	Seilbahner
Truck driver	Lastwagenführer
Automotive mechanic	Automobil-Fachmann
Sailor	Matrose in der Binnenschifffahrt
Catering professional	Restaurationsfachmann
Cook	Koch
Hotel specialist	Hotelfachmann
Professional housekeeper	Fachmann Hauswirtschaft
Stone sculptor	Steinbildhauer
Photography expert	Fotofachmann
Graphic designer	Grafiker
Textile designer	Textilentwerfer
Gold smith	Goldschmied
Wood carver	Holzbildhauer
Ceramist	Keramiker
Stained-glass artist	Glasmaler

Notes: List provided by the Berufsinformationszentrum and matched with SESAM.
Authors' translation.

Table A.3.3: Vocational occupations in Switzerland (continued)

Title of occupation	German title of occupation
Musical instrument maker	Musikinstrumentenbauer
Decoration designer	Dekorationsgestalter
Interior decorator	Innendekorateur
Social care worker	Fachmann Betreuung
Chemical and pharmaceutical technologist	Chemie- und Pharmatechnologe
Physics laboratory assistant	Physiklaborant
Medical practice assistant	Medizinischer Praxisassistent
Pharmaceutical assistant	Pharma-Assistent
Optician	Augenoptiker
Massage therapist	Medizinischer Masseur
Orthopaedic technician	Orthopädist
Dental technician	Zahntechniker
Dental assistant	Dentalassistent
Veterinary nurse	Tiermedizinischer Praxisassistent
Care assistant	Pflegeassistent
Healthcare worker	Fachangestellter Gesundheit
Textiles care worker	Textilpfleger
Building cleaner	Gebäudereiniger
Chimney sweeper	Kaminfeger
Plant maintenance expert	Fachmann Betriebsunterhalt
Recycling expert	Recyclist
Hairdresser	Coiffeur
Beautician	Kosmetiker
Podiatrist	Podologe
Logistician	Logistiker
Archivist	Fachmann Information
Theatre painter	Theatermaler

Notes: List provided by the Berufsinformationszentrum and matched with SESAM.
Authors' translation.

CHAPTER 4

A Declining Middle? The Relation between Changes in Skills and Wages of Middle-Skilled Wages

Part of this chapter is a revised version of early parts of the working paper “Skill Prices, Skill Composition, and the Structure of Wages” by Rinawi and Backes-Gellner (2015).

4.1 Introduction

This chapter analyzes educational outcomes in a dynamic setting. In the long run, market dynamics might lead firms to demand different types of skills. Workers, in turn, have to respond to changed skill demands. We investigate how skill requirements have changed over time and how these changes are related to changes in workers’ wages.

The United States and many European countries are witnessing substantial changes in their wage structure, attracting sustained attention of policy makers and the general public (Dustmann, Ludsteck, and Schoenberg 2009; Acemoglu and Autor 2011; Card, Heining, and Kline 2013). Most research has focused on changing returns to education and experience (Katz and Murphy 1992), changes in the workforce composition (Lemieux 2006b), or the decline in unionization (DiNardo, Fortin, and Lemieux 1996) as possible explanations for the observed changes. Until recently, little attention has been paid to the role of occupational skills.

With the pioneering work by Autor, Levy, and Murnane (2003), researchers started linking changes in the wage structure to the occupational structure of the economy, and particularly to the skill requirements of different occupations. The main idea is that changes in the wage structure within- and between occupations are systematically related changes in the types of skills[1] in these occupations. They hypothesize that technological changes have non-monotonic effects on the demand for skill over the wage distribution: They reduce the demand for routine tasks performed in middle-wage occupations, increase the demand abstract tasks performed in high-wage occupations, and have little direct impact on the demand for non-routine manual tasks used in many low-wage occupations.

This hypothesis has become known as “routinization,” or routine-biased technical change. In line with this hypothesis, researchers have consistently shown U-shaped changes in employment shares and wages, i.e., increasing employment shares and increasing wages at the top and the bottom and decreasing employment shares and decreasing wages in the middle (Autor, Katz, and Kearney 2006, 2008; Goos and Manning 2007; Goos, Manning, and Salomons 2009, 2014; Autor and Dorn 2013).

To date, however, empirical research has been largely limited to descriptive analyses.[2] Specifically, while previous findings suggest a potentially important role of skills, they do not analyze the relationship between changes in skills and changes in wages in a regression framework. Moreover, most studies assume a static view to describe skill requirements in occupations, thus not allowing for occupations to change their skill composition over time.[3] However, a much more plausible assumption is that the introduction of new technologies will not simply wipe out routine-task intensive occupations, but fundamentally change the tasks performed in these occupations. New technologies thus require new tasks, which substitute or complement the current tasks.

In this chapter, we address both shortcomings in the previous literature and quantify the contribution of changing skills to changes in the wage structure by explicitly accounting for within-occupation changes in skill requirements. For the empirical analysis, we use data from Germany. Our skills data are the BIBB/IAB and BIBB/BAuA Employment Surveys, representative cross-section surveys conducted roughly every seven years since 1979. Each survey wave contains questions on the types of skills needed on the job. We describe each occupation as a bundle of skills, distinguishing between cognitive, interactive, and manual skills. Within occupations, we are able to identify how the share of these skills changes over time. We match our skills data to the Sample of Integrated Labour Market Biographies (SIAB),

[1] We provide a detailed discussion on the difference between skills and tasks in the theory section of this chapter.
[2] Notable exceptions are Antonczyk, Fitzenberger, and Leuschner (2009) and Firpo, Fortin, and Lemieux (2011b).
[3] A notable exception is Spitz-Oener (2006).

a panel on complete job histories and wages. The SIAB is a two percent random sample of all social security records in Germany, covering the employment histories of about 1.5 million individuals from 1975 through 2008.

To explicitly quantify the contribution of changing skills to changes in wages over the whole wage distribution, we use the recently developed decomposition approach based on recentered influence function (RIF) regression by Firpo, Fortin, and Lemieux (2007). With this method, we move beyond merely describing changes in shapes but instead apply a regression framework to the question of how technological change impacts wages. Besides allowing for a quantification of the effects of skills, this method enables us to take into account that changes in skill requirements might affect wages differently at different parts of the wage distribution. In addition, this approach allows considering several explanatory factors simultaneously.

Germany is an important case for analyzing changes in the wage structure, because the evidence on wage polarization is far less clear than for other countries. Although earlier studies found a polarization of employment and wages attributable to the routinization of work (Spitz-Oener 2006; Dustmann, Ludsteck, and Schoenberg 2009), more recent studies started pointing out that findings for the United States and the United Kingdom cannot easily be transferred to Germany. Specifically, recent contributions hypothesize that the use of new machinery and computers complements the work of middle-skilled workers rather than substituting it (Bonin et al. 2015; Eichhorst und Buhlmann 2015; Moeller 2015). In the same vein, Eichhorst et al. (2015) show that, since the mid-1990s, employment shares of middle-skilled workers remained largely stable.

Because of this particular development, in our core analysis, we restrict our sample to middle-skilled workers and investigate changes in wages for this particular group. Moreover, both for low-skilled and for high-skilled workers the occupational profiles are much less clear cut than for the middle-skilled. While low-skilled workers do typically not receive any training beyond compulsory schooling, high-skilled are typically trained in university majors that are not easily transferable to one specific occupation.

Focusing the analysis on middle-skilled workers allows investigating the effects of changes within well-defined occupations and thus enables policy conclusions. Because in Germany about two thirds of the workforce holds a vocational degree, our analysis is taking into account the largest part of the labor market. As a robustness check, we run a separate analysis for the full sample and show that our findings remain largely unchanged.

In the first step of the analysis, we show that skill requirements varied substantially within- and between occupations. In particular, we see an overall increase in the importance of cognitive skills, while the importance of manual skills is decreasing. In addition, we show that the wage level and the dispersion of wages have changed substantially both for the restricted sample of middle-skilled workers and the whole population. In particular, we show that from the late 1970s through the late 1980s, changes in wages were mostly concentrated at the upper part. From the early 1990s through the mid-2000s, wages at the lower parts decreased, while wages at the upper part continued increasing. These patterns hold for both the reduced and the full sample. The patterns are largely similar to those found in previous studies that have used earlier versions of the German administrative records, in particular, Fitzenberger (1999), Gernandt and Pfeiffer (2007) and Dustmann, Ludsteck, and Schoenberg (2009).

In the second step, we perform RIF regression-based decompositions to investigate whether the observed changes in skills and wages are related. The decomposition method accounts for composition effects, i.e., changes in worker and job characteristics, and wage structure effects, i.e., changes in the returns to these characteristics. Our decomposition results suggest that wage structure effects were largely driving the changes in wages, while composition effects only played a minor role. Specifically, changes in the returns to skills were most pronounced during the 1990s and the mid-2000s. Increases in the returns to cognitive skills were mostly increasing top-end inequality, increasing wages of workers at the top of the distribution. Wages of workers in the middle of the distribution were increasing as well, due to both increases in cognitive and manual skills.

Changes affect upper- and lower-tail inequality differently because differently skilled workers are not uniformly distributed along the wage distribution: Positively affected workers are clustered in the upper part, whereas adversely affected workers are clustered in the lower part of the wage distribution. Our findings show that we cannot confirm the same U-shaped polarization patterns that studies for Anglo-Saxon countries have found. Rather, the lower part of the distribution has experienced wage losses, the middle has remained largely stable and has either gained or lost depending on the skill profiles, and the upper part has experienced wage gains.

Our analyses show that skill requirements within occupations vary substantially over time. It appears that most occupations do not simply become obsolete, but rather adapt to a changing technological regime by undergoing substantial changes in their skill requirements. Any discussion on how technological change affects the nature of work should thus explicitly account for changing skill requirements within occupations. In addition, quantifying the contribution of skills to changes in the wage structure allows a better understanding of why some occupations have experienced sharp decreases in wages, while others have experienced sharp increases. This chapter therefore adds two new theoretical dimensions to the recent discussions on technology-induced changes in the wage structure.

Finally, our results have crucial implications for the main research question of this doctoral thesis, namely, how to secure returns on educational investments in changing market environments. First, we provide empirical evidence that returns to skills vary over time and depend on market dynamics. Secondly, we are able to quantify exactly how returns to single skills vary within different occupations. Thirdly, we show that, unlike in the U.S. and the UK, middle-skilled workers in Germany have not experienced sharp declines in their wages. This finding could be interpreted as evidence that the dual vocational education and training system is enabling workers to well-adapt to technological change.

4.2 Theoretical Background

In this section, we first give an overview of the discussion in the literature on the differences between tasks and skills and on how to evaluate task and skill measures. Second, we briefly review recent literature that has investigated changes in the wage structure. Third, drawing on Firpo, Fortin, and Lemieux (2011), we introduce a wage setting model where changes in occupational wages depend on within-occupation changes in skill requirements and skill prices.

4.2.1 Defining Skills and Tasks

For the purpose of our discussion, it is essential to clarify the distinction between tasks and skills. Acemoglu and Autor (2011) define tasks as units of work activity that produce output, while skills are workers' endowments for performing various tasks. Workers apply their skills to carry out tasks in exchange for wages. This distinction is inconsequential if workers of a given skill always perform the same set of tasks. However, it becomes relevant when shifts in technology change the assignment of skills to tasks. Therefore, they argue that one needs to apply a model that is able to measure the mapping between skills and tasks and observe the changes in this mapping over time.

Acemoglu and Autor (2011) acknowledge that this skill-task mapping presents a substantial measurement challenge since consistent information on job tasks is generally not collected by representative data sources. Specifically, they point to the following shortcomings of the data most commonly used in the task literature, the Occupational Information Network (O*NET) and its predecessor, the Dictionary of Occupational Titles (DOT).[4]

First, the job content measures are often vague, repetitive, and constructed using ambiguous scales that are likely to confuse respondents. Second, and in line with what we have pointed out previously, the task measures offer a static view of the tasks an occupation comprises. Third, the sheer number of distinct occupations and the vast quantity of unique scales leads researchers essentially to pick and choose among the vast amount of information. Fourth, because in the O*NET it is not the workers themselves who report on the activities performed on the job, but rather occupational experts who assign scores to different indicators characterizing occupations, this data might underestimate the true changes in job content.

Most importantly, Acemoglu and Autor (2011) point out that the task definitions in the O*NET and DOT are somewhat inconsistent. Following Autor, Levy, and Murnane (2003), researchers have often used three broad task groups: routine cognitive and manual tasks, abstract analytical tasks, and non-routine manual tasks. While these task attributes are broadly distinct, there are important overlaps among them. For example, many routine cognitive tasks (e.g., performing calculations) also require abstract analytical tasks. How these overlaps should affect task classification remains an unresolved issue.

To avoid some of these pitfalls, Autor (2013) recommends collecting job task information directly from survey respondents. In this regard, he argues that the German BIBB/IAB and BIBB/BAuA Employment Survey and the British Skills Survey might be potential data sets that overcome the weaknesses of the U.S. data. However, whether the measures in these data are functionally equivalent to the U.S. measures is difficult to assess. Therefore, imposing the framework introduced by Autor, Levy, and Murnane (2003) to data other than the O*NET might lead to wrong classifications and wrong conclusions.

In recent contributions, Green (2012) compares the U.S. measures with the British data and Rohrbach-Schmidt and Tiemann (2013) do the same with the German data. Both studies show that for most of the measures in their respective data sets, there is no direct counterpart in the U.S. data. In that case, classification is up to the discretion of the researcher, which increases the potential for misclassification and makes reproducibility more difficult. In addition, both

[4] The O*NET is sponsored by the U.S. Department of Labor, Employment and Training Administration and provides hundreds of standardized descriptors with detailed information on knowledge, skills, abilities, and work activities of more than 800 occupations.

Green (2012) and Rohrbach-Schmidt and Tiemann (2013) point out that the classification of tasks as either routine or non-routine is especially problematic in their data.

To go into more detail with the German data, Rohrbach-Schmidt and Tiemann (2013) review Spitz-Oener's (2006) task classification and note that some of the tasks might be misclassified. Examples are "calculating" which is classified as a routine cognitive task, but could as well be a non-routine cognitive task given that the GED Math measure in the Autor, Levy, and Murnane (2003) paper includes the items "adds and subtracts 2-digit numbers." In addition, some items seem to include both routine and non-routine tasks. For instance, "measuring" includes measuring, testing, and quality control tasks. Whereas "measuring" can be considered a routine manual task, "testing" and especially "quality control" might also include non-routine manual tasks. Finally, they perform a sensitivity analysis in which they use a different operationalization for the task data. Their analysis shows that different classifications of tasks into the domains proposed by Autor, Levy, and Murnane (2003) lead to different conclusions on task changes in Germany. Therefore, they recommend researchers not to distinguish between routine and non-routine tasks.

Given these challenges, in this chapter, we decide not to follow the classification by Autor, Levy, and Murnane (2003) when using the German data. We decide following the suggestions by Rohrbach-Schmidt and Tiemann (2013) and instead do not draw a distinction between routine and non-routine tasks. Instead, we distinguish between cognitive, interactive, and manual tasks only. These three categories allow us to univocally assign all of the items listed in the surveys to one of the categories. The classification is straightforward and reduces classification ambiguity in the sense that for example calculating is simply classified as cognitive skill and there is no need for debating whether is it routine cognitive or non-routine cognitive. Our classification thus produces more easily replicable results because it uses only one dimension.

In addition, we assume a one-to-one mapping between skills and tasks. This assumption is reasonable for vocational occupations in Germany, where the content of the training curricula and the tasks performed on the job closely match and the large majority of workers are working in the occupations they were trained in. Unlike in the U.S., the German labor market has an institutionalized occupational structure, where occupations are structured according to the corresponding tracks of vocational qualifications and bound by vocational qualifications (Maurice, Sellier, and Silvestre 1982; Eyraud, Marsden, and Silvestre 1990; Marsden 1999). Given that training curricula are constantly updated, our assumption of a one-to-one mapping also holds for technology shifts. In addition, conflicting with the task approach, theories of search and matching predict that the matching of workers to occupations is very tight (Albrecht and Vroman 2002; Wong 2003). Therefore, in our application, we could use the terms skill and task interchangeably as they both measure the same. We decide to use the term skill exclusively to avoid any confusion with the task-based approach of Autor, Levy, and Murnane (2003).

4.2.2 Technological Change and Wages

In the early 1990s, a series of studies argued that technological change alters the demand for skilled work (Bound and Johnson 1992; Katz and Murphy 1992; Levy and Murnane 1992; Juhn, Murphy, and Pierce 1993; Berman, Bound, and Griliches 1994; Machin and van Reenen 1998). These studies introduced the concept of a skill-biased technological change (SBTC), defined as a shift in the production technology that favors skilled over unskilled workers by increasing their relative productivity. The working hypothesis was that a burst of new technology caused a rise in the demand for highly skilled workers, which in turn led to a rise in earnings inequality. However, the actual U.S. wage development is not easily reconciled with the SBTC idea. Since the late 1980s, wages in the middle of the distribution stagnated, while wages of the lowest and highest percentiles of the wage distribution increased.

More recently, a new literature has introduced a more “nuanced” view of the SBTC (Autor, Levy, and Murnane 2003). Instead of years of education, this new literature uses an alternative measure for skills, based on detailed descriptions of job content and skills requirements. Similar to Lazear’s skill weights-approach (2009), the nuanced view of the SBTC posits that occupations are characterized by a bundle of single tasks. The main idea is that the introduction of information technologies has not simply depressed the relative demand for less educated workers, but instead changed the demand for certain types of skills required on the job.

Autor, Katz, and Kearny (2006), Goos and Manning (2007), and Autor and Dorn (2013) argue that this nuanced view of technological change can account for the polarization of wages that has been observed since the late 1980s. In particular, they argue that the adoption of computers substitutes tasks performed in middle-wage jobs, while increasing the demand for tasks performed in low-wage and high-wage jobs. Autor, Katz, and Kearney (2006) provide evidence that the share of employment in occupations in the middle of the wage distribution has declined over time in the United States. Similarly, Goos and Manning (2007) show that the composition effect linked to changes in the distribution of occupations accounts for a substantial part of the increase in inequality in the United Kingdom. Using a spatial equilibrium approach, Autor and Dorn (2013) show that local labor markets that are more specialized in routine jobs experienced more job polarization.

For the case of Germany, it was long believed that the country was characterized by a stable wage distribution (Steiner and Wagner 1998). However, recent work has shown that wage inequality started increasing already in the 1980s and accelerated in the 1990s and 2000s (Gernandt and Pfeifer 2007; Dustmann, Ludsteck, and Schoenberg 2009; Fuchs-Schuendeln, Krueger, and Sommer 2009; Card, Heining, and Kline 2013). Whether the nuanced view of the SBTC serves as an explanation for the rise in the German wage dispersion remains a contested issue.

Specifically, in line with the SBTC view, Spitz-Oener (2006) shows that, between 1979 and 1999, changes in skill requirements have been strongest in occupations in which computerization was most pronounced. Similarly, Dustmann, Ludsteck, and Schoenberg (2009) argue that the SBTC is the main driver of wage inequality in the 1980–2000 period in West Germany. However, their actual empirical results are more mixed: They show that employment shares of occupations at the top of the wage distribution increased, employment shares of occupations in the middle of the wage distribution declined, and employment shares of occupations at the low end did not change. This pattern does not reflect the Anglo-Saxon pattern, where employment shares at the low end increased quite dramatically and have led to the well-known polarization.

Antonczyk, Fitzenberger, and Leuschner (2009) and Antonczyk, deLeire, and Fitzenberger (2010) conclude that some of the developments of German employment shares might be explained by a decline in routine tasks. However, they point out that great differences exist between the developments in the US and Germany and that the SBTC alone cannot fully explain the empirical results for Germany. Finally, Boockmann and Steiner (2006) actually find a decline in the returns to education. However, they do not use occupational skills as a skill measure, but instead use years of schooling.

In our analysis, we try to resolve these conflicting results by taking into account different explanations for why the German wage dispersion has increased. We do not introduce the SBTC as an alternative, but rather as a complimentary explanation. Our unique data and the novel methodological approach allow us to consider several explanatory factors simultaneously. Before explaining our econometric strategy, we will briefly introduce the wage-setting model by Firpo, Fortin and Lemieux (2011) to clarify the connection between skills and wages.

4.2.3 Wage Setting in Occupations

Most of the literature on the impact of technological change on wages follows a traditional Mincer approach where wages are determined by observed and unobserved skills. This model features two distinct skill groups—college and high school workers—performing two distinct and imperfectly substitutable tasks or producing two imperfectly substitutable goods. Technology is assumed to take a factor-augmenting form, meaning that it complements either high- or low-skilled workers and thus induces skill-biased demand shifts. In this way, the college/high school wage ratio, for example, reflects the premium that high-skilled workers receive relative to low-skilled workers. The premium is determined by the relative supply of and relative demand for skills. The relative demand for skills increases over time because changes in technology are assumed to be "skill-biased," in the sense that new technologies have greater demands for highly skilled workers. However, since relative supply has also steadily increased, this leads to Tinbergen's (1974) famous race between technology and the supply of skills.

Acemoglu and Autor (2011) refer to this model as the "canonical model." This model is not only tractable and conceptually attractive but has also proved empirically successful in explaining the evolution of skill premiums in the U.S. throughout the twentieth century. However, the canonical model does not provide satisfactory explanations for a number of empirical developments of more recent years. For example, it cannot explain differential changes in inequality in different parts of the wage distribution. To overcome these weaknesses in light of the observed changes in the U.S. wage structure over the past four decades, Acemoglu and Autor (2011) and Firpo, Fortin, and Lemieux (2011) propose new wage-setting models.

Acemoglu and Autor (2011) propose a model that incorporates a clear distinction between skills and tasks and allows the assignment of skills to tasks to be determined in equilibrium by labor supply, technology, and task demand. Tasks can be performed by workers with different types of skills or by machines, so that certain tasks can become mechanized. To understand how different technologies affect skill demands, wages, and the assignment of skills to tasks, their model allows for comparative advantage among workers in performing different types of tasks. Because of the crucial role comparative advantage differences across different types of workers play in the model, Acemoglu and Autor refer to their model as a Ricardian model of the labor market.

They assume a pattern of comparative advantage such that tasks are ranked in order of complexity. Medium-skilled workers are more productive than low-skilled workers, and less productive than high-skilled workers in more complex tasks.[5] Workers with different levels of skills are systematically allocated to different occupations on the basis of their comparative advantage. The equilibrium allocation is determined by two thresholds, such that low-skilled workers perform all tasks below the lower threshold, high-skilled workers perform all tasks above the higher threshold, and medium-skilled workers perform all intermediate tasks. Critically, the law of one price holds within each skill group in the sense that wages are equalized across occupations, conditional on skill.

However, this assumption of uni-dimensional task allocation and thus a law of one price is unlikely to hold in reality. What is observable in the data is that low-, middle-, and high-skilled workers also overlap in their tasks and in their task complexity.[6] In the empirical application, Acemoglu and Autor (2011) therefore drop all task categories that have these overlaps. This drop is quite substantial so that they use only seven instead of 16 O*NET scales. They do, however, not discuss how to reconcile the empirical findings with their theoretical model and whether or not the exclusion of categories limits the generalizability of their results. Their empirical application shows that allowing for different skill-weights across occupations is indeed crucial for understanding the wage setting in occupations. Assuming a law of one price makes sense if each occupation required one skill only. However, because the data shows that occupations require skill bundles with differing skill weights, we need to apply a wage-setting model that allows wages to vary according to the required skill bundle.

Lazear (2009) first introduced the idea of skill-weights. Firpo, Fortin, and Lemieux (2011) use this idea and propose a wage-setting model with much less restrictive assumptions. Relative to Acemoglu and Autor (2011), they go one step further by allowing wages to vary across occupations conditional on the skills of workers, as in a standard Roy model. They cite a wide range of empirical evidence in support of the Roy model. For example, Heckman and Scheinkman (1987) show that wages systematically differ across sectors even after controlling for observed and unobserved skills. Gibbons et al. (2005) reach a similar conclusion when looking at both industry and occupation wage differentials. In addition, a number of other reasons might explain why wages fail to equalize across occupations, conditional on skill.

The most prominent example is the discussion about occupation-specific human capital, which initiated the task-based approach. Therefore, we decide to use the more adequate model proposed by Firpo, Fortin, and Lemieux (2011), which allows wages to vary across occupations.

[5] However, this assumption does not necessarily hold for labor markets characterized by vocational occupations. Therefore, applying this model to the German context might proof to be challenging.

Formally, Firpo, Fortin, and Lemieux (2011) assume that each worker *i* is characterized by a k-dimension set of skills $S_i = [S_{i1}, S_{i2}, \dots, S_{iK}]$. The amount of occupation-specific output Y_{ijt} produced by worker *i* in occupation *j* is assumed to depend linearly on skills:

$$\mathrm{Y_{ijt}} = \sum_{\mathrm{k=1}}^{\mathrm{K}} \alpha_{\mathrm{jkt}} \mathrm{S_{ik}} \tag{4.1}$$

where the productivity α_{jkt} is occupation- and time-specific. In this model, each occupation requires different shares of different types of skills. Researchers, for example, require a large share of cognitive skills and a rather small share of manual skills. In contrast, machinists require the opposite configuration of skills.

In this framework, factors such as technological change have a different impact on wages in different occupations. If the introduction of computer technologies increases the marginal product of cognitive skills for researchers, both the level and the dispersion of their wages should increase. If computers depress the returns to skills, a symmetric pattern emerges. For example, if automated machines decrease the marginal product of manual skills of machinists, then the level and the dispersion of wages should decrease. Importantly, if manual skills are not a highly valued skill for researchers, then the change in the skill price for manual skills does not affect researchers' wages.

In contrast to Firpo, Fortin, and Lemieux (2011), we assume productivity to vary over time. Assuming that wages are set competitively, workers are paid for the output they produce, yielding the following wage equation:

$$w_{ijt} = \theta_{jt} + \textstyle\sum_{k=1}^{K} r_{jkt} Y_{ijt} + u_{ijt}, \tag{4.2}$$

where w_{ijt} is the wage of worker *i* in occupation *j* at time *t*, r_{jkt} are the returns to the skills component *k* specific to occupation *j* at time *t*, Y_{ijt} is the output produced in occupation *j* at time *t*, and θ_{jt} is a base payment that a worker receives in occupation *j* regardless of his skills.

This simple model predicts that wages might change due to changes in skill prices r_{jkt} or due to changes in productivity α_{jkt}. In principle, we could treat the wage-setting equation like a structural model and estimate its parameters. However, we use a simpler and less parametric approach by carrying out decompositions at each point of the wage distribution.

4.3 Data

For our empirical analysis, we combine the Sample of Integrated Labor Market Biographies (SIAB) with the BIBB/IAB and BIBB/BAuA Employment Surveys. The first data provides the wage data, while the second data provides the skill information. In this section, we introduce both data sources and show descriptive analyses on how skill requirements and wages changed over the last three decades.

4.3.1 The Sample of Integrated Labour Market Biographies

Our main data set is a two percent random sample of administrative social security records in Germany from 1975 through 2008, covering the employment histories of more than 1.5 million individuals. The SIAB is representative of all individuals covered by social security, which is roughly about 80 percent of the German workforce. It includes total earnings, days worked at each job in a year, as well as information on education, occupation, industry, and part-time or full-time status. Importantly, occupational titles are constant over the observation period so that we can analyze changes in wages within occupations over time.

We use occupational titles at the two-digit level for three main reasons. First, we need to obtain a sufficiently large number of observations for each occupation to perform the econometric analysis. Second, to maintain comparability of results, we follow previous literature in this field, which almost exclusively uses two-digit occupations. Third, and most importantly, occupations at higher digit levels do not greatly differ from each other in terms of the aggregated skill bundles that we use. For example, the three-digit level distinguishes between “nursing aides (671),” “paramedics (672),” and “ambulance drivers (673),” whereas at the two-digit level these occupations are summarized under “nursing aides (67).” In terms of their skill bundle, it is reasonable to assume that nursing aides, paramedics, and ambulance drivers have large overlaps in their shares of cognitive, interactive, and manual skills, whereas they differ greatly from their neighboring occupations “nursing and elder care (66)” as well as “body and beauty care (68).”

As in many administrative data sets, our data is right-censored at the highest level of earnings. Overall, each year between 9.4 percent and 14.2 percent of the male wage distribution is censored. However, once we restrict our sample to workers with a vocational education and training (VET) degree, censoring becomes a less severe problem with only about three percent of censored wages. To solve the censoring problem, we follow a method proposed by Gartner (2005) and use a series of Tobit models—fit by education level, industry, and region—

to stochastically impute the upper tail of the wage distribution. While we use the imputed wages for the descriptive analyses, our decomposition analysis focuses on the uncensored part of the wage distribution.

Although we are specifically interested in the wages of VET workers, of course we have to relate wages of this particular population to the overall population. The VET population might have been changing over time with different ability types selecting in or out of VET programs. If this were the case, our effects might be biased due to a different cohort mix in different years. In addition, given that we want to verify whether wages of middle-skilled workers remained stable over time, we have to look at wage changes at both the top and the bottom of the skill distribution. We conduct separate analyses, where we include all educational degrees in the sample. Results for the full sample are reported in the Appendix in Tables A.4.1 through A.4.6. We find no large differences between the two samples. In the full sample, the wage dispersion is slightly larger. In addition, the effect size of the skill measures is generally smaller. These results can be expected given that the full sample also captures the between education dispersion and includes education variables as additional explanatory variables.

At both the beginning and the end of the periods we analyze, we pool several years of data together to improve the precision of the estimates. We use 1978/79 as the base year and 1985/86 as the end year for the first period we analyze; 1985/86 as the base and 1991/92 as the end year for the second period, 1991/92 and 1998/99 for the third, and 1998/99 and 2005/06 for the last period. These periods are chosen to match the cross-sectional waves of the BIBB/IAB Employment Surveys that contain the skills data.

The econometric analyses focus on men. The labor force participation of women has increased considerably over the observed period and this increase is likely to have changed the selection of women into work. Because of this selection issues, we cannot perform longitudinal analyses on female wages and compare them to male wages. In the descriptive analysis, however, we investigate the wage structure for both men and women.

For our main analysis, we follow Dustmann, Ludsteck, and Schoenberg (2009) and focus on full-time employed[7] men between 21 and 65 years of age who are subject to social security contributions. Because both the level and the structure of wages differ substantially between

[7] Because the SIAB does not include hours of work, limiting our attention to full-time workers reduces the impact of the hours dispersion that could confound trends in wage inequality. However, less than seven percent of male workers in the SIAB have no full-time job in a year, so the inclusion of wages for part-time men has only a small impact on the trends we study.

East and West Germany, we use West German data only. Moreover, following Riphahn and Schnitzlein (2011), we drop all observations for which daily wages are below 12 euros.

Table 4.1 presents some basic characteristics of our wage data across the four observation periods.[8] Reported wages are log gross daily wages weighted by the number of days worked in a respective year. Wages are reported in euros and deflated to 1978 wages, the first year of the analysis. The table shows that the average wages of full-time men rose by about five percent between 1978 and 1986, again rose by about another five percent between 1986 and 1992, slowed down by rising one percent over the next eight years and remained relatively stable in the 2000s. Average wages of full-time women rose by about four percent between 1978 and 1986, then increased more sharply and rose by nine percent between 1985 and 1992, rose by another five percent between 1992 and 1999, and then stabilized at a level about 25 log points below the mean for men. The standard deviation of log wages for both genders rose slightly between 1978 and 1992, then surged over the next years, rising by five log points between 1992 and 1999 and another five log points between 1999 and 2006 for men. For women, the increase happened with a time gap. The standard deviations of log wages rose by two log points in the 1990s and rose by another five log points between 1999 and 2006.

Table 4.1: Descriptive statistics of the VET sample

		Log real wages	
	Observations	Mean	St. Dev.
Panel A. Men			
1978-79	240,929	3.740	0.230
1985-86	241,016	3.783	0.260
1991-92	268,288	3.833	0.266
1998-99	249,818	3.849	0.305
2005-06	224,001	3.839	0.347
Panel B. Women			
1978-79	103,633	3.416	0.390
1985-86	120,849	3.459	0.403
1991-92	155,533	3.544	0.409
1998-99	145,407	3.598	0.428
2005-06	126,778	3.580	0.475

Notes: Sample includes employees in West Germany, aged 20-60, working full-time. Wages are based on average daily earnings, in euro, and deflated to 1978 wages. Wages that are centered at social security maximum are stochastically allocated based on a Tobit model. SIAB data 1978-2006, authors' calculations.

[8] Table A.4.1 in the Appendix presents wage data for the full sample.

4.3.2 Wage Patterns

In the following section, we discuss the wage patterns of the four periods for both male and female workers. Figures 4.1 and 4.2 show the distributional characteristics of changes in the wage structure for both male and female workers.[9] We plot the fitted values of the difference in log wages between two periods over the whole distribution. The vertical line shows the median wage change. The descriptive patterns give a first indication for why we need to perform distributional analyses to understand the wage dynamics. A simple analysis of the mean or median wage would miss the large changes that occurred at the top and the bottom ends of the distribution.

The figures show that from 1978/79 to 1985/86 wages increased overall. However, changes in wages were mostly concentrated at the upper part of the distribution, with sharp increases beyond the eighth decile. Between 1985/86 and 1991/92, wages continued increasing, but the size of the increase was much smaller than in the previous period. Wages were mostly increasing in the middle of the distribution, and at the top and the bottom ends the increases were much less pronounced.

The 1990s paint a different picture. While the median wage remained almost unchanged, wages below the fourth decile decreased, while wages above the fourth decile increased. At the lower part of the distribution, wages fell by about five percent. In contrast, above the 80th percentile, wages increased by between five and ten percent. Finally, from 1998/99 to 2005/06, wages continued decreasing sharply below the median, while they continued increasing again above the median. While wages decreased between five and 10 percent below the third decile, they increased by about eight percent above the eighth decile.

The descriptive patterns largely hold for both male and female workers, although female wages changed more sharply. A striking difference between the wage patterns of male and female workers is that females did not experience wage losses during the 1990s, while male workers did. This pattern might be due to occupational sorting. Because women typically refrain from sorting into occupations that require large shares of manual skills, they may have been less affected by decreasing returns to manual skills and might have profited more from increasing returns to cognitive skills.

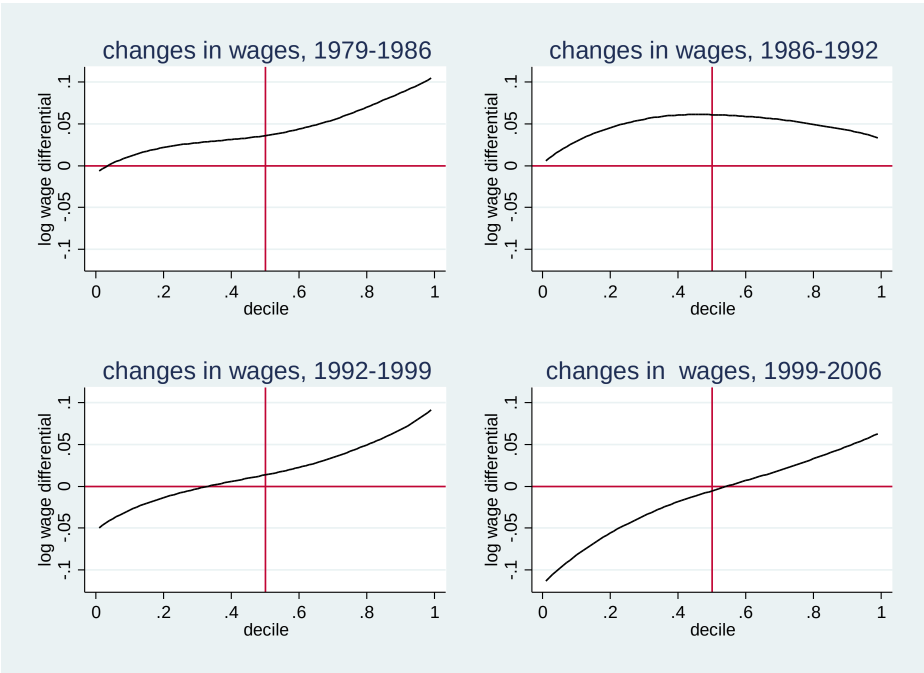
Figures A.4.1 and A.4.2 in the Appendix show the patterns for the full sample, which are largely similar to those of the restricted one. However, from the 1990s onwards, wage losses at

[9] The wage patterns of the full sample are reported in the Appendix (Figures A.4.1 and A.4.2).

the lower end and wage increases at the upper end were more pronounced in the full sample. These results indicate that, on average, unskilled workers, who are concentrated at the lower part of the wage distribution, suffered higher wage losses than middle-skilled workers. Contrarily, high-skilled workers, who are concentrated at the upper part of the distribution, gained more than middle-skilled workers.

These wage patterns for the full sample show polarization tendencies, but they are not the same as in Anglo-Saxon countries. While the U.S. and the UK see increasing wages for the top and the bottom and decreasing wages for the middle of the distribution, the middle in Germany remains largely stable, while workers at the lower part suffer wage decreases and workers at the upper part of the distribution experience wage gains.

Figure 4.1: Changes in log wages by percentile, male workers with a VET degree, 1978 to 2006



Notes: Sample includes male employees in West Germany with a VET degree, aged 20-60 and working full-time. Wages are based on average daily earnings, in euro, and deflated to 1978 wages. Wages that are centered at social security maximum are stochastically allocated based on a Tobit model.
SIAB data 1978-2006, authors' calculations.

Figure 4.2: Changes in log wages by percentile, female workers with a VET degree, 1978 to 2006

Notes: Sample includes female employees in West Germany with a VET degree, aged 20-60 and working full-time. Wages are based on average daily earnings, in euro, and deflated to 1978 wages. Wages that are centered at social security maximum are stochastically allocated based on a Tobit model.
SIAB data 1978-2006, authors' calculations.

4.3.3 BIBB/IAB and BIBB/BAuA Employment Surveys

The BIBB/IAB and BIBB/BAuA Employment Surveys on Qualification and Working Conditions (hereafter: BIBB/IAB Employment Surveys) are representative surveys among fully employed individuals in Germany. From 1979 to 1999, the survey was conducted by the Federal Institute for Vocational Education and Training (BIBB), together with the Institute for Employment Research (IAB), and thereafter in cooperation with the Federal Institute for Occupational Safety and Health (BAuA). For our analysis, we use four different waves: 1979, 1985/86, 1991/92, 1998/99, and 2006, each covering about 30,000 individuals.

The BIBB/IAB Employment Surveys report on the content of occupations and the education backgrounds of employees. They are particularly suitable for analyzing changes in skill requirements within occupations since occupations are categorized in all waves according to the classification of the German Federal Employment Bureau in 1988.[10] This is a major improvement over, for example, the American O*NET and its predecessor, the DOT, the data

[10] We use the two-digit level of classification, which includes about 50 different vocational occupations and an additional 20 occupations in the full sample including occupations of unskilled workers and workers with a tertiary education degree. We provide a list of these occupations in the Appendix, Table A.4.7.

most commonly used for studying skills and occupations, where occupational titles do not remain constant over time.

To ensure compatibility with our SIAB sample, we restrict the BIBB/IAB data in a number of ways. For our main analysis, we follow Dustmann, Ludsteck, and Schoenberg (2009) and Gathmann and Schoenberg (2010) and focus on full-time employed men in West Germany between 18 and 65 years of age.[11] The reasoning behind this sample restriction is the following. First, we exclude women, because their labor force participation has increased considerably over the observed period and this increase is likely to have changed the selection of women into work. Second, we exclude East Germany, because before 1990, neither the SIAB nor the BIBB/IAB provide data on East Germany. Moreover, after the re-unification in 1990, both wage and employment levels differ substantially between East and West Germany.

Third, we exclude part-time workers, because they might differ from fulltime workers in both required skills and wages. Fourth, we exclude the unemployed, because they have zero wages and might remember skill requirements differently from what is actually required. Fifth, we exclude the self-employed in the BIBB/IAB data, as these individuals are not included in the SIAB data. Moreover, we exclude workers with agricultural occupations or working in the agricultural sector, because the observations are not representative for these workers in either data set. Finally, we have to restrict the BIBB/IAB sample to employees with German nationality, since foreign nationals were not interviewed in the 1979 and 1986 waves of the BIBB/IAB Employment Surveys.

The survey contains a large number of questions on education with a particular focus on vocational education and training, making the survey especially suitable for studies of middle-skilled workers. The respondents are asked to report on a large set of skills that are required for

[11] While our sample is representative for the majority of male workers in West Germany, we are not able to judge whether our results also apply to certain groups of workers that we exclude from the analysis. If these workers were clustered in certain occupations, our results might be biased for those occupations. We analyse the data descriptively to check whether this clustering occurs for part-time workers, female workers, and workers resident in East Germany. In the 1970s and 1980s, the occurrence of part-time work was very small (below 2% for most occupations). In the 1990s and 2000s, the share of part-time workers increased, although not uniformly across occupations. In the 1990s, receptionists and janitors were among the occupations with the highest share of part-time work (10% - 15%), whereas in the 2000s it was cashiers and cleaners (around 20%). Overall, part-time work does not appear to be very common (especially given that we exclude female workers), so that we have no reason to worry about excluding these workers. Concerning female workers, we find a strong clustering over time for some occupations. Throughout the observation period, the following occupations had a share of female workers of 95% or higher: receptionists, kindergarten teachers, hair dressers, dieticians and typists. If female and male workers were to significantly differ in terms of skills and wages in these occupations, then our findings would clearly not be representative. However, we do not claim that our results apply to female workers as well. Finally, concerning East Germany, we find a high clustering for track layers, bricklayers, pavers, and roofers (25% - 45%). Thus, if we were to include East Germany, we would probably find different results for these occupations.

performing their current job. Many of the survey questions remain unchanged between two waves, but not all skill items are included in all waves. To compare skills over time, in the decomposition analysis, we follow Spitz-Oener (2006) and focus on those questions that remain unchanged during the periods we are investigating.

However, the content and importance of certain skills change over the observation period. Take IT and programming skills as an example. Questions on IT skills were included in most waves and we classify them as cognitive skills throughout our observation period, given that they always involve abstract-logical thinking and technical understanding. But, because it is also true that the nature of IT skills changes over this long period, we choose to run pair-wise comparisons of two consecutive waves, instead of running panel regressions.

We quantify changes in IT skills over a period of roughly eight years (e.g. from 1998/99 until 2005/06), and identify changes in the price and the composition of these skills. We are confident that the nature of IT skills remains constant over this relatively short time. Because the understanding of what IT skills are should not change over that time, our results should not be driven by measurement error. Descriptively, we can show changes in skill requirements over the entire observation period. Econometrically, we compare two waves with each other and can exactly quantify changes in skill prices and composition.

We distinguish between three skill categories: cognitive, interactive, and manual skills. As pointed out previously, this classification reduces ambiguity and allows a univocal assignment of the items listed in the surveys to one of the skill categories. Cognitive skills include reading and calculating, interactive skills include negotiating and supervising. Manual skills do not mean manual in the traditional sense of e.g., fine motor skills, but more in the sense of doing things. In our category, they include for example equipping and using machinery, and repairing and renovating.

Because the unit of analysis is the occupation, we aggregate the individual data into occupational cells and use group means for our decomposition analyses. Similarly to Spitz-Oener (2006) and Antonczyk, Fitzenberger, and Leuschner (2009), we first define skills at the individual level and then aggregate them to the occupational level. For individual *i* at time *t*, we define a skill category *s* as:

$$s_{ict} = \frac{number\ of\ skills\ in\ category\ c\ required\ by\ i\ at\ time\ t}{total\ number\ of\ skills\ required\ by\ i\ at\ time\ t} \tag{4.3}$$

where t = 1979, 1985/86, 1991/92, 1998/99, and 2006 and category c = 1 (cognitive skills), c = 2 (interactive skills), and c = 3 (manual skills). To generate a skill category at the occupational level, we sum the individual skill categories s_{ict} in each occupation and divide them by the number of observations in that occupation.

Table 4.2 shows the three categories. While in the descriptive part, we aggregate all skill requirements that fall into one of the three categories, in the econometric analysis we condition on those skills that remain unaltered from one wave to the other. This allows us to quantify how the returns to those skills has changed over time.

Table 4.2: Classification of skills

Category	**Skills**
Cognitive skills	calculating; designing; educating, guiding and teaching; evaluating, testing and verifying; journalistic work; programming; writing
Interactive skills	coordinating and planning; assessing and investigating; applying rules; counseling; managing personnel; negotiating; organizing
Manual skills	equipping and operating machinery; repairing, renovating and reconstructing; manufacturing, installing or constructing; nursing; securing

Notes: BIBB/IAB Employment Surveys, 1979-2006, authors' translation.

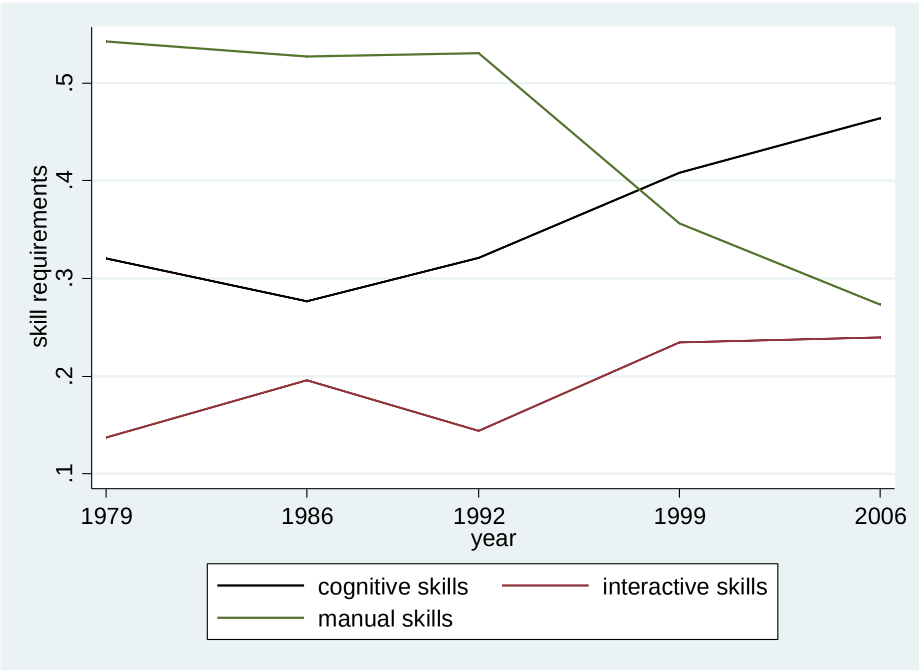
4.3.4 Skill Patterns

Figures 4.3 and 4.4 show the changes in skills requirements over time for men and women respectively. More precisely, they show the share of skills used across all occupations at different points in time. The most striking feature of these patterns is that, as expected, skill requirements have changed dramatically over time. In the male sample, occupations required about 30 percent of cognitive skills, 15 percent of interactive skills, and 55 percent of manual skills in 1979, while in 2006 they required 50 percent of cognitive skills, 30 percent of interactive skills, and an average of about 20 percent of manual skills. In the female sample, occupations required about 40 percent of cognitive skills, 10 percent of interactive skills, and about 60 percent of manual skills in 1979. Contrarily, in 2006, occupations required about 55 percent of cognitive skills, 25 percent of interactive skills, and 20 percent of manual skills.

These figures already show that for any analysis relating occupational skills to changes in wages it is pivotal to take into account that skill measures are not static, but subject to continuous updating and re-allocating.

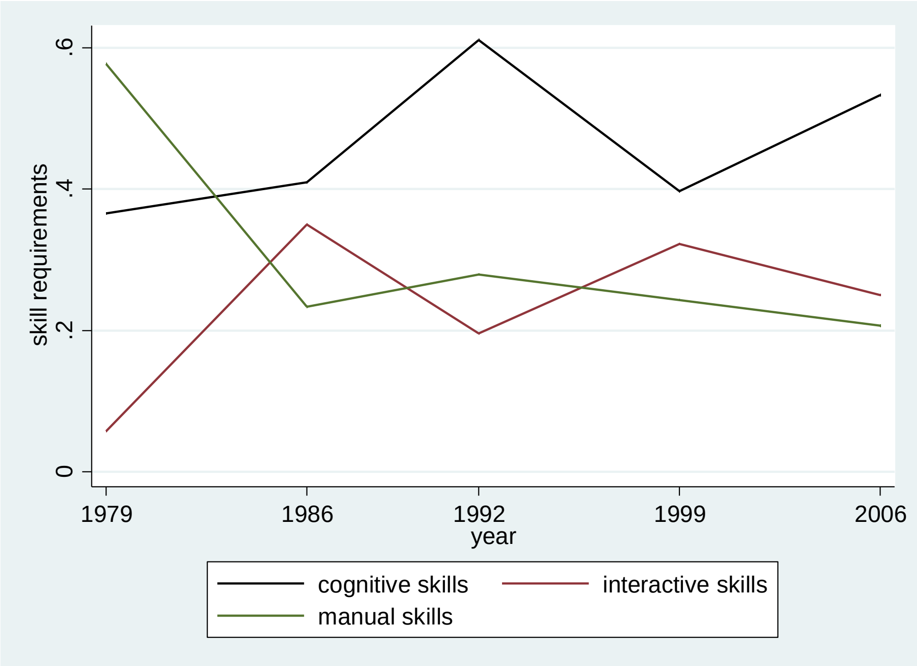
In the male sample, cognitive skills have been constantly rising since 1986, with the sharpest increases in the 1990s. Interactive skills have remained more or less stable, slightly increasing since the 1990s. In contrast, manual skills remained at a constantly high level of about 50 percent until the beginning of the 1990s and have then decreased sharply, falling to below 30 percent in 2006. For the female sample, the pattern is somewhat different, which is most likely due to the fact that men and women select into different types of occupations. The share of cognitive skills has started increasing earlier than in the male sample, already rising since 1979. After 1992, however, this share remained constant at about 55 percent. The share of interactive skills surged in the early 1980s, decreased again in the late 1980s, and has been rising since 1992. In 2006, the share of interactive skills makes up about 25 percent of all skill requirements. Finally, the share of manual skills decreased very sharply between 1979 and 1986. From then on it remained more or less stable at a share of about 20 percent.

Figure 4.3: Changes in skill requirements, male workers with a VET degree, 1979 – 2006



Notes: Sample includes male employees in West Germany with a VET degree, aged 18-65, and working full-time. BIBB/IAB Employment Surveys, 1979-2006, authors' calculations.

Figure 4.4: Changes in skill requirements, female workers with a VET degree, 1979 – 2006



Notes: Sample includes female employees in West Germany with a VET degree, aged 18-65, and working full-time. BIBB/IAB Employment Surveys, 1979-2006, authors' calculations.

4.4 Econometric Model: RIF Regression-Based Decomposition

In the empirical analysis, we decompose changes in the wage structure into their contributing factors. Understanding the factors accounting for differences in the distribution of individuals' economic outcomes across two periods, or between subgroups of the population is central in several fields of economic research, particularly in labor economics. The Oaxaca-Blinder decomposition (Oaxaca 1973; Blinder 1973) is the most commonly used decomposition method in the labor economics literature (for an overview of the literature see Weichselbaumer and Winter-Ebmer (2005) and for a comprehensive overview of the application see Jann (2008)).

This technique decomposes mean differences in log wages in a counterfactual manner. It develops counterfactual wages, that is, estimates of mean wages with changed underlying population characteristics. It divides the wage differential between two groups into a part that is explained by observable group characteristics ("composition effect") such as education or experience and a residual part ("wage structure effect") that cannot be accounted for by these differences. The residual part measures the returns to observable characteristics.

Before going more into detail, we should note one important feature of decomposition methods. While decompositions are useful for quantifying the contribution of different factors to a difference in outcomes such as the wage differential between two groups, they cannot provide information on the underlying mechanism between factors and outcomes. Just like program evaluation methods, decompositions provide valuable information about which factors are quantitatively important in a particular relationship, but they cannot provide information on the structural parameters of that relationship. They can thus be considered as a first important step in investigating a relationship.

For example, if the decomposition shows that a large part of the gender wage gap can be accounted for by differences in the occupational affiliation, then, in the second step, this suggests exploring in detail how men and women choose their fields of study and occupations. In our application, we perform the decompositions to explore whether skills are important in explaining changes in the wage structure. If we find important differences, in the second step, our results may suggest exploring in detail how workers choose to acquire certain types of skills both during their initial vocational education and further training.

The Oaxaca-Blinder decomposition is easy to apply and only requires coefficient estimates from linear regressions for the outcome of interest and sample means of the independent variables used in the regressions. However, it focuses on the difference in the mean of an outcome variable and does not allow decompositions along the wage distribution. Until recently, no comprehensive approach was available for computing a detailed decomposition of the effect of single covariates for a distributional statistic other than the mean. In a recent contribution, Firpo, Fortin, and Lemieux (2009) (hereafter: FFL) have introduced an approach that allows taking into account the whole unconditional wage distribution. Their approach is very similar in spirit to the Oaxaca-Blinder decomposition in the sense that it allows decomposing the distributional statistic of interest into a wage structure and a composition effect and further dividing the wage structure and composition effects into the contribution of single covariates.

FFL’s central idea is to use the recentered influence function (RIF) regression for the distribution statistic of interest as the left hand side variable in a regression.[12] The procedure consists of two steps. In the first step, FFL use a reweighting method to divide the distributional differences between two groups into a wage structure effect and a composition effect. In the second step, they further decompose the wage structure effect and the composition effect into the contribution of each explanatory variable using RIF regression. FFL explain in great detail

[12] Riphahn and Schnitzlein (2011) use the SIAB data to apply RIF regression-based decompositions when studying wage mobility in East and West Germany.

how to perform these decompositions. Here, we will present a short summary of their methodology.

In general, any distributional parameter can be expressed as a functional $\nu(F_y)$ of the cumulative distribution of wages, $F_Y(Y)$. To formally discuss the RIF-based decomposition method, let us look at the difference in the wage distributions during two periods, 1 and 0. For individual i, let Y_{1i} be the wage that he would receive in period 1 and Y_{oi} the wage received in period 0. For each i, we can define the observed wage, Y_i, as $Y_i = Y_{1i} * T_i + Y_{0i} * (1 - T_i)$, where $T_i = 1$ if the individual is observed in period 1 and $T_i = 0$ if the individual is observed in period 0. The notation $F_{Y_{t|T=s}}$ denotes the distribution of wages that would prevail among workers observed in period s if they were paid under the wage structure of period t. Therefore, $F_{Y_{0|T=0}}$ indicates the actual distribution in period 0, and $F_{Y_{1|T=1}}$ denotes the actual distribution in period 1. In contrast, $F_{Y_{0|T=1}}$ denotes the counterfactual distribution that would have prevailed if workers in period 1 had been paid under the wage structure of period 0.

Consider Δ_O^ν, the overall change over time in the distributional statistic ν. We have:

$$\begin{aligned}\Delta_{\mathrm{O}}^{\nu} &= \nu(\mathrm{F}_{\mathrm{Y}_1|\mathrm{T}_1}) - \nu(\mathrm{F}_{\mathrm{Y}_0|\mathrm{T}_0}) \\ &= \nu(\mathrm{F}_{\mathrm{Y}_1|\mathrm{T}_1}) - \nu(\mathrm{F}_{\mathrm{Y}_0|\mathrm{T}_1}) + \nu(\mathrm{F}_{\mathrm{Y}_0|\mathrm{T}_1}) - \nu(\mathrm{F}_{\mathrm{Y}_0|\mathrm{T}_0}),\end{aligned} \tag{4.4}$$

where the first difference is the unexplained part of the decomposition, which Oaxaca-Blinder coined as the wage structure effect, Δ_S^ν. The second difference is the explained part of the decomposition, which they coined as the composition effect, Δ_X^ν. The wage structure effect reflects that part of the wage differential that cannot be explained by differences in the distribution of observable characteristics, but is attributable to changes in the returns to these characteristics. The composition effect reflects that part of the wage differential that can be explained by differences in the distribution of covariates.

Put differently, while the wage structure effect reflects the difference in the *β's*, the decomposition effect reflects the differences in the distribution of the *X's* and *ε's* between the two groups. In our analysis, the *X's* comprise the three skill categories: cognitive, interactive, and manual skills. In addition, we include a vector of control variables observed in all periods. Our controls include age and experience and their squared terms, and industry and region dummies.

Combing back to the equation, $\nu(F_{Y_0|T_1})$ is the counterfactual distributional statistic that would have prevailed if workers observed in period 1 had been paid under the wage structure of period 0. As noted previously, to estimate this type of counterfactual distribution, FFL suggest using the approach by DiNardo, Fortin, and Lemieux (1996), which consists of estimating a probit model on the probability of being observed in period 1. In essence, it consists of reweighting the period 0 data to have the same distribution of X*'s* as in period 1.[13] The reweighted data allows performing Oaxaca-Blinder type decompositions and obtaining the wage structure and the composition effects for any distributional statistic.

If we were interested solely in wage structure and composition effects, we could simply apply the reweighting method by DiNardo, Fortin, and Lemieux (1996) and would not need to bother with the FFL procedure. However, we are interested in separating the contribution of single explanatory variables to see whether one of them is driving the effects. To further decompose the wage structure and the composition effect into the contribution of single covariates, an additional step is needed. FFL suggest performing RIF regressions on the reweighted data.

The central idea of the RIF is to replace the dependent variable y by the corresponding recentered influence function. Essentially, recentering means adding back the distributional statistic to the influence function. Let $IF(y;\ \nu)$ denote the influence function corresponding to an observed wage y for the distributional statistic of interest ν. The recentered influence function (RIF) is defined as:

$$\mathrm{RIF}(\mathrm{y}; \mathrm{q}_\tau) = \mathrm{q}_\tau + \mathrm{IF}(\mathrm{y}; \mathrm{q}_\tau). \tag{4.5}$$

We can compute this influence function for a large number of different distributional statistics. For our case, we use quantiles. The recentered influence function of the τ*-th* quantile is:

$$\mathrm{RIF}(\mathrm{y}; \mathrm{q}_\tau) = \mathrm{q}_\tau + \mathrm{IF}(\mathrm{y}; \mathrm{q}_\tau). \tag{4.6}$$

The τ*-th* quantile RIF regression aggregates to the unconditional quantile of interest and captures both the within and between effects of the explanatory variables. The crucial advantage of this approach is that it provides a tool to estimate the effects of the covariates on the

[13] Firpo, Fortin, and Lemieux (2007) show that this reweighting provides a consistent nonparametric estimate of the counterfactual distribution.

unconditional distribution of wages.[14] We then perform the decomposition by running two standard Oaxaca-Blinder decompositions on the estimated coefficients of the recentered influence functions. The first decomposition compares period 0 with the reweighted period 0 (that mimics period 1) and allows obtaining the composition effect. The second decomposition compares period 1 with the reweighted period 0, allowing us to obtain the pure wage structure effects.

FFL show that we can write the estimate of the composition effect $\hat{\Delta}^{\nu}_{X,R}$ as:

$$\widehat{\Delta}^{\nu}_{X,R} = (\overline{X}_{01} - \overline{X}_{0})\,\hat{\gamma}^{\nu}_{0} + \overline{X}_{01}(\hat{\gamma}^{\nu}_{01} - \hat{\gamma}^{\nu}_{0}) = \widehat{\Delta}^{\nu}_{X,p} + \widehat{\Delta}^{\nu}_{X,e} \tag{4.7}$$

We thus divide the composition effect, $\hat{\Delta}^{\nu}_{X,R}$, into a pure composition effect, $\hat{\Delta}^{\nu}_{X,p}$, using the wage structure of period 0 and into a component measuring the specification error, $\hat{\Delta}^{\nu}_{X,e}$. Similarly, we can write the wage structure effect as:

$$\widehat{\Delta}^{\nu}_{X,S} = \overline{X}_{1}(\hat{\gamma}^{\nu}_{1} - \hat{\gamma}^{\nu}_{01}) + (\overline{X}_{1} - \overline{X}_{01})\hat{\gamma}^{\nu}_{01} = \widehat{\Delta}^{\nu}_{S,p} + \widehat{\Delta}^{\nu}_{S,e}, \tag{4.8}$$

which reduces to the first term, because the reweighting error $\widehat{\Delta}^{\nu}_{S,e}$ goes to zero as $\overline{X}_{01} \rightarrow \overline{X}_{1}$.

In sum, the formulas for the different components of our decomposition procedure are the following:

$$Total\ Change: \widehat{\Delta}^{\nu}_{O} = \overline{\widehat{RIF(Y_1},\nu)} - \overline{\widehat{RIF(Y_0},\nu)}$$

$$Composition\ Effect: \widehat{\Delta}^{\nu}_{X,p} = (\overline{X_{01}} - \overline{X_{0}})\widehat{\gamma^{\nu}_{0}}$$

$$Wage\ Structure\ Effect: \widehat{\Delta}^{\nu}_{S,p} = \overline{X_{1}}(\widehat{\gamma^{\nu}_{1}} - \widehat{\gamma^{\nu}_{01}})$$

[14] The difference between conditional and unconditional quantile regression is best explained through an example. Assume that X is a dummy variable indicating college versus high-school attendance and the outcome variable is earnings. If we estimate a quantile regression for $\beta(50)$ the correct interpretation of $\hat{\beta}(\theta)$ is not the effect of college attendance on the 50th percentile wage earner. Rather, it is the effect of college attendance on the 50th percentile of the wage distribution. In the case of unconditional quantile regression, $\hat{\beta}(\theta)$ is the effect of college attendance on the 50th percentile wage earner.

4.5 Results

We use the decomposition approach of Firpo, Fortin, and Lemieux (2009) to quantify the contribution of single explanatory factors to changes in the wage distribution. These factors comprise our three skill measures as well as age and experience and their squared terms, region and industry dummies. In line with previous research, we focus our analyses on men.

As we have pointed out previously, this decomposition method consists of two steps. In the first step, we use a reweighting method to recover the counterfactual wage distribution. With the reweighted data we can decompose the wage difference into a wage structure and a composition effect. FFL call these decomposition results “aggregate decomposition results.” In the first subsection we present these aggregate results. In the second step, we perform RIF regressions on the reweighted data and then perform Oaxaca-Blinder decompositions on the RIF coefficients.

This second step is a crucial methodological innovation, which allows obtaining the detailed decomposition results. Only this additional step allows quantifying the contribution of single explanatory variables to changes in the wage structure. Put differently, it allows quantifying which type of skills contributes to the observed changes in wages by how much and at which parts of the distribution. This exact quantification allows assessing whether changes in skills even play an important role, what role they play (increasing or decreasing inequality), and whether changes in some skills have larger impacts than changes in other skills.

4.5.1 Aggregate Decomposition Results

To simplify the discussion, we focus on standard measures for wage inequality. We report changes over time in the 90-10 log wage differential as a measure for overall inequality, and changes in the 90-50 and the 50-10 log wage differential as measures of upper-tail and lower-tail wage inequality. A widening of these gaps implies an increase in wage inequality.

Table 4.3 reports the aggregate decomposition results for our VET sample. In the first step of our discussion, we focus on the analysis of how wage inequality changes over the considered period. In the second step, we look into which effects are driving the changes.[15] Overall, the results are consistent with the descriptive analyses in Section 4.3.2, which indicates that our model provides a reasonable fit. From 1978 to 1986, overall wage inequality increases by about six log points, whereby almost all of the increase in the wage gap is due to a wage increase in

[15] The effect sizes and significance levels are similar to the ones reported in Firpo, Fortin, and Lemieux (2011b).

the upper tail of the wage distribution. Between 1986 and 1992, overall wage inequality remains largely stable. However, bottom-end inequality increases by almost three log points, while top-end inequality decreases by about two log-points.

From the beginning of the 1990s until the end of our observation period in 2006, wage inequality surges. During the 1990s, overall inequality increases by eight log points, whereby top-end inequality increases by about five log points and bottom-end inequality increases by about three log points. From 1999 to 2006, overall inequality increases further by another 12 log points. Top-end inequality increases by about another five log points and bottom-end inequality increases by about seven log points.

These changes translate into the following real wage changes, with real wages being daily wages deflated to 1978 wages and expressed in euros. During the observation period, median wages increases from 43 euros in 1978 to 47 euros in 2006. At the first decile, wages decrease from 32 euros to 30 euros, while at the ninth decile, wages increase from 56 euros to 71 euros. As pointed out previously, also the standard deviation of wages increases during the observation period. The standard deviation is 23 percent in 1978 and increases to about 35 percent in 2006.

The question now arises as to which factors contribute to these developments. Table 4.3 divides the total wage change into the composition effect—due to group differences—and the wage structure effect—the residual part that cannot be accounted for by group differences. Both effects contribute significantly to the observed changes over all four periods, although the wage structure effect is generally much larger in size. Given that our restricted sample of male VET workers is largely homogenous, it makes sense that the composition effects do not play a very important role.

Table A.4.2 in the Appendix shows that for the full sample, starting in the 1990s, composition effects account for an important part of the increase in wage inequality. This result is in line with findings by Dustmann, Ludsteck, and Schoenberg (2009), who point out that the breakdown of the communist regimes in Eastern Europe as well as the reunification of East and West Germany led to a large inflow of East Germans and Eastern Europeans into the West German labor market. This inflow led to great changes within the workforce composition, which is reflected in the composition effects.

Combing back to the analysis of our restricted sample in Table 4.3, during the first observation period, from 1978 to 1986 (Panel A), most of the changes in wage inequality happen at the upper part of the distribution. Wage structure effects are driving the increase in wage inequality, accounting for slightly more than 100 percent of the increase, whereas decomposition effects move into the opposite direction, i.e., decreasing wage inequality. That composition effects and wage structure effects might cancel each other out is a common finding in the literature (see Firpo, Fortin, and Lemieux (2011) and Riphahn and Schnitzlein (2011)).

These effects (Panel A, column 2, row 2 and 3) suggest that changes in the distribution of the underlying characteristics of the population only play a minor role and are actually decreasing inequality at the top, whereas the returns to these underlying characteristics are increasing, thereby fueling top-end inequality. This could mean, for example, that the returns to certain types of skills or to experience are increasing at the upper part of the distribution over the considered period.

From the mid-1980s to the beginning of the 1990s (Panel B), we observe that overall wage inequality hardly changes. The wage gap increases slightly at the lower part of the distribution and decreases slightly at the upper part, so that the overall effect is minimal. Increases in the 50-10 gap are mostly attributable to composition effects. This means that changes in the distribution of underlying characteristics increase the 50-10 gap.

This could mean, for example, that the share of inexperienced workers with low wages increases during that period, thereby increasing wage inequality. At the top end, decreases in the wage gap are mostly attributable to wage structure effects. This means that the returns to the underlying characteristics are decreasing, thereby decreasing the 90-50 gap. However, the coefficient of the wage structure effect is rather small (-0.0171) so that overall changes in the returns to the underlying characteristics seem negligible in our second observation period.

Form the beginning of the 1990s until the mid-2000s (Panels C and D), wage inequality increases sharply, increasing by eight log points between 1991 and 1999, and by another 11 log points between 1999 and 2006. During the 1990s (Panel C), lower-tail inequality increases by about three log points, whereby most of this increase is driven by wage structure effects. This could mean, for example, that changes in the returns to skill increase during this period, widening the gap between workers with different skill bundles in the lower part of the distribution.

Upper tail inequality increases by about five log points, whereby the increase is driven both by wage structure effects and composition effects. This could mean, for example, that changes in the returns to skill increase at the upper part of the distribution. At the same time, changes in the distribution of underlying characteristics also increase the upper-tail wage gap. An explanation for this pattern could be that the returns to certain types of skills might have increased disproportionally so that workers with large shares of these skills experience large wage gains, increasing the 90-50 gap.

From 1999 to 2006 (Panel D), lower-tail inequality increases by about seven log points, whereby most of this increase is again driven by wage structure effects. Upper tail inequality increases again by about five log points, whereby the increase is also mostly driven by wage structure effects. These results point towards great changes in the returns to underlying characteristics. Again, this could mean that changes in the returns to different types of skills are increasing wage inequality.

However, as pointed out previously, the aggregate decomposition results neither provide information about the contribution of single covariates nor about the underlying mechanism. They only provide a broad picture of what is going on and point the researcher towards the economically significant effects. We need to perform the second step of the RIF-regression based decomposition to quantify the contribution of single variables.

Comparing the aggregate decomposition results for our sample of VET workers to the decomposition results for the full sample reported in the Appendix in Table A.4.2 shows that changes in the wage structure are very similar. Overall, the increase in wage inequality is somewhat larger in the full sample. This result can be expected given that the full sample also captures the between-education wage dispersion.

As pointed out previously, while the relative size and the direction of wage structure effects are similar in the two samples, composition effects contribute to a larger extent to increasing wage inequality in the full sample. Finally, the full sample shows that the increasing wage inequality can be traced back to an increase in wages at the upper part of the distribution and a decrease in wages at the bottom part. Thus, in contrast to the United States and the United Kingdom, West German wages in the middle of the distribution remain largely stable.

Table 4.3: Aggregate decomposition results

Inequality Measure	90-10	90-50	50-10
A: 1978/79 to 1985/86			
Total Change	0.0571*** (0.00016)	0.0503*** (0.00014)	0.0068*** (0.00031)
Composition	-0.0007*** (0.00009)	-0.0184*** (0.00031)	0.0177*** (0.00040)
Wage Structure	0.0578*** (0.00012)	0.0687*** (0.00038)	-0.0109*** (0.0005)
B: 1985/86 to 1991/92			
Total Change	0.0091*** (0.00025)	-0.0173*** (0.00015)	0.0264*** (0.00040)
Composition	0.0273*** (0.00035)	-0.00001*** (0.00009)	0.0274*** (0.00044)
Wage Structure	-0.0181*** (0.00033)	-0.0171*** (0.00024)	-0.0010*** (0.00057)
C: 1991/92 to 1998/99			
Total Change	0.0804*** (0.00040)	0.0524*** (0.00020)	0.0280*** (0.00060)
Composition	0.0369*** (0.00065)	0.0299*** (0.00049)	0.0070*** (0.00114)
Wage Structure	0.0437*** (0.00071)	0.0228*** (0.00056)	0.0209*** (0.00127)
D: 1998/99 to 2005/06			
Total Change	0.1163*** (0.00055)	0.0482*** (0.00026)	0.0681*** (0.00081)
Composition	0.0285*** (0.00042)	0.0113*** (0.00001)	0.0172*** (0.00043)
Wage Structure	0.0878*** (0.00051)	0.0369*** (0.00034)	0.0509*** (0.00085)

Notes: SIAB data linked with BIBB/IAB Employment Surveys.
Standard errors are in parentheses.
Significance levels: * < 0.1; ** < 0.05; *** < 0.01.

4.5.2 Detailed Decomposition Results

Tables 4.4 to 4.7 show the detailed decomposition results for the four periods we are investigating. We examine the explanatory power of our skill categories in the context of a formal decomposition of changes in the wage distribution. To simplify the discussion, the tables report only the single effects of our three skills categories and group the effects of the control variables in individual- and firm-specific controls. We recur to the aggregate decomposition results as guidance for the economic significance of the effects under investigation. While the aggregate decomposition results inform us about the size of the overall wage structure and composition effects, the detailed decomposition results inform us about the contribution of single explanatory variables in explaining wage structure and composition effects.

Table 4.4 presents the decomposition results for the period 1978/79 to 1985/86. The table shows that our skill categories have non-monotonic effects, a typical feature of the RIF regression. Changes in skills increase wage inequality at some parts of the distribution, while they decrease inequality at other parts. Panel A shows the detailed composition effects and Panel B shows the detailed wage structure effects.

To understand the single drivers for the changes in wages, the composition and the wage structure effects of single explanatory variables have to be analyzed together, i.e., to comprehend the effect of changes in, for example, cognitive skills, one needs to look at both at how cognitive skills have changed in the underlying distribution of the population (composition effects) and how the returns to cognitive skills have changed (wage structure effects).

Panel A shows that changes in the composition of cognitive and interactive skills are associated with an increase in inequality over the entire distribution. An explanation for this observation could be that, between 1978 and 1986, the number of individuals with large shares of cognitive or interactive skills has increased and that these skills are also more highly rewarded. In contrast, changes in the composition of manual skills decrease overall inequality and account for almost all of the decrease of the 90-50 gap (Panel A, Column 2).

This observation goes hand in hand with the fact that changes in the returns to manual skills explain a large part of the increase of the 90-50 gap (Panel B, Column 2). The number of individuals with large shares of manual skills might have decreased, which narrows the 90-50 gap. Differences in workers' skill bundles become less important, because the returns to manual skills are still increasing. However, given that the overall composition effects are minimal and slightly decreasing inequality (Panel A, column 1, row 6), we infer that these skill effects are counter-balanced by other factors such as changes in the age- or experience composition during this period.

Panel B shows that the returns for all of our three skill categories increase during the observation period. The increase is most pronounced at the upper part of the wage distribution, where increases in the returns to skills account for almost all of the wage structure effect. Table 4.3 (Panel A, Column 2) indicates how relevant wage structure effects are in this period. The estimated wage structure effects account for more than 100 percent of the increase in the 90-50 gap. As pointed out previously, that these effects might exceed 100 percent is common in the literature, because composition and wage structure effects might cancel each other out. Increases in the returns to all of the three skill categories are thus the main drivers of wage inequality at the upper part of the distribution. However, Table 4.3 (Panel A, Column 3) shows that at the lower part of the distribution, wage structure effects are actually decreasing wage inequality. Here, the increasing returns to skills that we see in Table 4.4 are counter-balanced by decreasing returns to other characteristics such as age or experience.

We can summarize the results for changes in wages between 1978 and 1986 as follows: First, the population in 1986 shows greater differences in workers' skill profiles than the population in 1979. Along the whole distribution, changes in the possession of cognitive and interactive skills increase wage inequality. Essentially, this means that some workers acquire these skills while others do not and this difference fuels inequality. At the same time, changes in the acquisition of manual skills increase inequality at the lower part of the distribution, while they decrease inequality at the upper part.

This means that, at the lower part of the distribution, workers' skill profiles differ along the manual dimension and fuel inequality, whereas at the upper part workers become more similar in terms of their manual skills, thereby decreasing inequality. In terms of economic significance it is most important to stress that increases in the returns to manual and cognitive skills increase wage inequality. These results confirm that increases in the returns to skills play an important role in increases in upper-tail wage inequality from 1978 to 1986. Our descriptive analyses reveal that this increase in upper-tail inequality is mostly driven by an increase in wages at the very top of the distribution.

Finally, a comparison to the full sample (table A.4.3 in the Appendix) shows that size and direction of the effects are very similar in both samples. The only exceptions are wage structure effects at the bottom-end of the distribution. While wage structure effects are slightly decreasing the 50-10 gap in the VET sample (-0.011), they are slightly increasing the 50-10 gap in the full sample (+0.008). Given that the detailed decompositions show that the returns to skills increase the 50-10 gap in both samples, changes in the returns to other characteristics must explain this difference. As pointed out previously, it is conceivable that increasing returns to skills in the VET sample are counter-balanced by decreasing returns to other characteristics such as age or experience.

Table 4.4: Detailed decomposition results, 1978/79-1985/86

Inequality Measure	90-10	90-50	50-10
A: Detailed Composition Effects			
Cognitive Skills	0.0140***	0.0060***	0.0080***
	(0.00002)	(0.00007)	(0.00005)
Interactive Skills	0.0125***	0.0056***	0.0069***
	(0.00004)	(0.00008)	(0.00004)
Manual Skills	-0.0111***	-0.0115***	0.0004***
	(0.00004)	(0.00022)	(0.00027)
Individual Controls	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes
Total Composition Effect	-0.0007***	-0.0184***	0.0177***
	(0.00009)	(0.00031)	(0.00040)
B: Detailed Wage Structure Effects			
Cognitive Skills	0.0195***	0.0117***	0.0077***
	(0.00009)	(0.00011)	(0.00020)
Interactive Skills	0.0071***	0.0048***	0.0022***
	(0.00006)	(0.00010)	(0.00016)
Manual Skills	0.0331***	0.0211***	0.0120***
	(0.00012)	(0.00033)	(0.00045)
Individual Controls	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes
Total Wage Structure Effect	0.0578***	0.0687***	-0.0109***
	(0.00012)	(0.00038)	(0.00050)

Notes: SIAB data linked with BIBB/IAB Employment Surveys.
Standard errors are in parentheses.
Significance levels: * < 0.1; ** < 0.05; *** < 0.01.

Table 4.5 presents the decomposition results for the period 1985/86 to 1991/92, when upper-tail inequality slightly decreases and lower-tail inequality slightly increases. Again, Table 4.3 provides guidance for the importance of the effects. Composition effects are increasing wage inequality over the whole distribution and thereby offsetting wage structure effects, which are decreasing wage inequality. Overall, the effect sizes of composition and wage structure effects are small compared to the effect sizes during other observation periods.

Panel A in Table 4.5 shows that all three skill measures contribute to a closing of the wage gap. This finding means that workers' skill profiles become more similar over the whole distribution. Even if these effects are highly statistically significant, they are very small in size. Therefore, composition effects are largely driven by other factors such as for example changes in the age and experience composition of the underlying population.

Panel B in Table 4.5 shows that the effect sizes of changes in the returns to skills are equally small. At the bottom end (50-10), decreases in the returns to cognitive skills are decreasing the wage gap. Combining this finding with the findings from the previous period, we see how returns to different skills change differently in different periods. Specifically, while the demand for cognitive skills exceeds the supply in earlier years from 1978 to 1986, in later years, from 1986 to 1992, supply appears to have caught up and changes in returns to cognitive skills play hardly any role anymore.

A comparison with the full sample (table A.4.4 in the Appendix) shows that size and direction of both composition and wage structure effects of our skill measures are very similar for both samples. The main differences are the composition effects. While they are minor for the VET sample, they increase the 50-10 gap by about three log points and decrease the 90-50 gap by about three log points in the full sample. Note that, also in the full sample, the effect sizes for our skill measures are negligible. Here, between 1986 and 1992, underlying characteristics of the population other than skills play a more important role in changing wage inequality.

We conclude that during the first two observation periods, i.e., from 1978 to 1992, at the upper part of the distribution, workers appear to have become more similar in terms of their underlying characteristics such as age and experience. The same holds true for workers' skills, although the effects are rather small and appear to play only a minor role. At the lower part of the distribution, workers appear to have become more dissimilar in terms of their underlying characteristics. Here again, however, the effects of changes in the underlying composition of skills are not the main driver for the increase in wage inequality.

In terms of changes in returns to skills, at first, increases in the returns to cognitive skills are increasing wage inequality mostly at the top of the distribution, while increases in the returns to manual skills increase wages in the middle of the wage distribution, increasing bottom-end inequality. This increasing return to manual skills indicates that these types of skills are increasing in importance in some occupations and that the increasing demand could not be matched by an adequate supply. However, eventually, the supply of manual skills catches up so that over the next period changes in returns to manual and cognitive skills are negligible.

Table 4.5: Detailed decomposition results, 1985/86-1991/92

Inequality Measure	90-10	90-50	50-10
A: Detailed Composition Effects			
Cognitive Skills	-0.0047***	-0.0023***	-0.0024***
	(0.00003)	(0.00006)	(0.00003)
Interactive Skills	-0.0168***	-0.0110***	-0.0058***
	(0.00015)	(0.00009)	(0.00024)
Manual Skills	-0.0006	-0.0003***	-0.0002
	(0.00004)	(0.00002)	(0.00006)
Individual Controls	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes
Total Composition Effect	0.0273***	-0.00001***	0.0274***
	(0.00035)	(0.00009)	(0.00044)
B: Detailed Wage Structure Effects			
Cognitive Skills	-0.0029	0.0009**	-0.0039
	(0.00020)	(0.00018)	(0.00038)
Interactive Skills	-0.0035***	0.0042***	-0.0077***
	(0.00026)	(0.00019)	(0.00045)
Manual Skills	-0.0028***	-0.0038***	0.0010***
	(0.00012)	(0.00011)	(0.00023)
Individual Controls	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes
Total Wage Structure Effect	-0.0181***	-0.0171***	-0.0010***
	(0.00033)	(0.00024)	(0.00057)

Notes: SIAB data linked with BIBB/IAB Employment Surveys.
Standard errors are in parentheses.
Significance levels: * < 0.1; ** < 0.05; *** < 0.01

Table 4.6 shows the decomposition results for the period 1991/92 to 1998/99, when both upper-tail and lower-tail inequality are increasing. Panel A shows that changes in the composition of skills are small in size and therefore largely negligible. The only exceptions are changes in the composition of interactive skills at the 90-50 gap. Combining this finding with our earlier observations reveals the patterns of a hog cycle (Ezekiel 1938; Hanau 1928) in the fluctuations of supply of different types of skills. It appears that individuals are adapting their skill bundles to changing demands. However, the time lags of this adaptation are too great so that the prices of the skills do not change accordingly.

Because the demand for cognitive and manual skills exceeds the supply in earlier periods, returns are high and individuals start investing more in acquiring these types of skills. During the 1990s, supply appears to have caught up so that changes in the underlying composition of workers' skills are negligible. Instead, the shortage is concentrated in interactive skills. These results might indicate that workers have been too focused on acquiring manual and cognitive skills, leading to an undersupply of interactive skills. However, as pointed out previously, the decomposition analysis only quantifies effects and does not allow a causal identification of mechanisms.

In Panel B, the wage structure effects show that we do not observe a perfect hog cycle, because changes in prices follow a different pattern. The wage structure effects are much more interesting in terms of economic significance, because they account for more than 100 percent of the increase in wage inequality that is due to changes in wage structure effects. While increasing returns to interactive and manual skills contribute rather modestly to an increase in the 90-50 gap, increasing returns to cognitive skills explain almost all of the increase. For the 50-10 gap, both increasing returns to cognitive skills and increasing returns to manual skills explain almost all of the increase.

To summarize, the 1990s are characterized by an increase in both upper-tail and lower-tail wage inequality. In terms of the distribution of underlying characteristics, most remarkably, changes in the composition of interactive skills are increasing the 90-50 gap. This result might be explained through a catching up effect. In terms of changing returns to skills, increases in returns to cognitive skills contribute to almost all of the increase of the 90-50 gap as well as to the increase of the 50-10 gap. In addition, also increases in the returns to manual skills account for a large part of the increases in the 50-10 gap.

The classification of skills in Table 4.2 gives an overview of the single skills that are summarized in our skill categories. Cognitive skills comprise e.g., calculating, writing, designing and planning. All of these activities might be complemented with new technology. Therefore, it is plausible that increases in the returns to cognitive skills might be traced back to technological changes, which increase the demand for cognitive skills. Manual skills comprise e.g., equipping and operating machinery and installing and constructing.

Although these activities primarily need some kind of technical knowledge, they too, could be complemented with new technologies. Therefore, also increases in the returns to manual skills might be traced back to technological changes. To equip and operate machinery, workers first need to have the basic technical knowledge. New technology might then complement their activities. That the increases in returns to cognitive skills are most pronounced at the upper part of the distribution might be due to the fact that workers with large shares of these skills select into high-wage occupations that require large shares of cognitive skills. Similarly, that the increases in returns to manual skills are most pronounced in the middle of the distribution might be due to the fact that workers with large shares of these skills select into middle-wage occupations that require large shares of manual skills.

Finally, Table A.4.5 in the Appendix shows the decomposition results for the full sample. Again, the results for the full sample are similar to those of the VET sample, both in direction and size of the effects. However, as pointed out previously, composition effects in the full sample are largely increasing wage inequality, while they play a minor role for the VET sample.

Table 4.6: Detailed decomposition results, 1991/92-1998/99

Inequality Measure	90-10	90-50	50-10
A: Detailed Composition Effects			
Cognitive Skills	-0.0112***	-0.0051***	-0.0061***
	(0.00010)	(0.00010)	(0.00020)
Interactive Skills	0.0353***	0.0267***	0.0086***
	(0.00039)	(0.00034)	(0.00073)
Manual Skills	0.0020***	0.0104***	-0.0084***
	(0.00056)	(0.00046)	(0.00102)
Individual Controls	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes
Total Composition Effect	0.0369***	0.0299***	0.0070***
	(0.00065)	(0.00049)	(0.00114)
B: Detailed Wage Structure Effects			
Cognitive Skills	0.0353***	0.0156***	0.0197***
	(0.00057)	(0.00042)	(0.00099)
Interactive Skills	0.0062***	0.0043***	0.0019***
	(0.00018)	(0.00012)	(0.00030)
Manual Skills	0.0408	0.0054***	0.0354
	(0.00096)	(0.00074)	(0.00170)
Individual Controls	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes
Total Wage Structure Effect	0.0437***	0.0228***	0.0209***
	(0.00071)	(0.00056)	(0.00127)

Notes: SIAB data linked with BIBB/IAB Employment Surveys.
Standard errors are in parentheses.
Significance levels: * < 0.1; ** < 0.05; *** < 0.01.

Table 4.7 presents the decomposition results for our final period, 1998/99 to 2005/06, when both lower-tail and upper-tail inequality continue rising. Panel A shows the composition effects. Similar to the 1990s, the composition effects of our skill measures are very small. However, the total composition effects (Panel A, row 6) show that the underlying characteristics of the population, in terms of characteristics such as age and experience, have been diverging. Just like in the 1990s, the effect sizes are, however, moderate: Composition effects raise top-end wage inequality by about one log point and bottom-end inequality by about two log points.

Panel B shows the wage structure effects, which are again more interesting in terms of economic significance. At the upper part of the distribution, increases in the returns to cognitive skills are driving almost all of the wage structure effects, while changes in the returns to other types of skills are unimportant. This finding shows how the trend of the 1990s continues through the mid-2000s. At the upper part of the distribution, changes in the returns to cognitive skills account for almost all of the changes in wage inequality. This finding might indicate that, since the beginning of the 1990s, the demand for cognitive skills has been increasing and workers at the upper part of the distribution, who mostly use cognitive skills, receive substantial wage increases.

Changes in returns to manual skills show a different pattern. While the returns to manual skills decrease at the upper part of the distribution, they largely increase at the lower part of the distribution and account for almost all of the increase in lower tail wage inequality. This development indicates that manual skills decrease in importance for occupations at the upper part of the distribution, while they increase in importance for occupations in the middle. As pointed out previously, due to the nature of the decomposition analysis, we can only speculate about the factors increasing or decreasing returns to different types of skills, but cannot provide a causal interpretation.

Finally, the results for the full sample (table A.4.6 in the Appendix) show similar patterns to those just described for the VET sample: Changes in the composition of skills hardly affect changes in the wage structure. With regards to the composition effects, factors other than skills are the main drivers of inequality. Changes in the returns to skills, on the other hand, are the main drivers for wage inequality over the whole distribution. Increasing returns to cognitive skills increase wages at the upper part of the distribution, thereby increasing the 90-50 gap. Increasing returns to manual skills increase wages at the middle of the distribution, thereby increasing the 50-10 gap.

Table 4.7: Detailed decomposition results, 1998/99-2005/06

Inequality Measure	90-10	90-50	50-10
A: Detailed Composition Effects			
Cognitive Skills	0.0016*** (0.00013)	0.0025*** (0.00009)	-0.0010*** (0.00022)
Interactive Skills	-0.0006*** (0.00002)	-0.0003*** (0.00002)	-0.0003*** (0.00001)
Manual Skills	-0.0067*** (0.00018)	0.0063*** (0.00011)	-0.0129*** (0.00029)
Individual Controls	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes
Total Composition Effect	0.0285*** (0.00042)	0.0113*** (0.00001)	0.0172*** (0.00043)
B: Detailed Wage Structure Effects			
Cognitive Skills	0.0341*** (0.00099)	0.0358*** (0.00065)	-0.0017*** (0.00164)
Interactive Skills	-0.0020*** (0.00140)	-0.0060*** (0.00094)	0.0040*** (0.00234)
Manual Skills	0.0486** (0.00075)	-0.0070*** (0.00049)	0.0556** (0.00124)
Individual Controls	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes
Total Wage Structure Effect	0.0878*** (0.00051)	0.0369*** (0.00034)	0.0509*** (0.00085)

Notes: SIAB data linked with BIBB/IAB Employment Surveys.
Standard errors are in parentheses.
Significance levels: * < 0.1; ** < 0.05; *** < 0.01.

4.6 Conclusion

West Germany has experienced substantial changes in the wage structure over the past three decades. During this time, also the skill structure of occupations has drastically changed. In this chapter, we relate these changes in skills to the observed changes in the wage structure. We combine long-running register data with longitudinal skill information. The skills data allows constructing time-variant occupational skill bundles and analyzing skills and wages in a dynamic setting. We apply straightforward and uni-dimensional skill measures, distinguishing between cognitive, interactive, and manual skills.

In the empirical analysis, we decompose changes in wages into their contributing factors, using the RIF regression-based decomposition introduced by Firpo, Fortin, and Lemieux (2009). This decomposition method consists of two steps. In the first step, we use a reweighting method to divide the distributional differences between two groups into wage structure effects and composition effects. In the second step, we further decompose the wage structure effects and the composition effects into the contribution of single explanatory variables using RIF regression. These steps allow moving beyond mere descriptive statistics and breaking down observed wage changes into changes due to varying worker characteristics and changes in the returns to those characteristics. This exact quantification allows assessing the role that changes in skills have played in recent changes in the wage structure.

In our main analysis, we perform the decompositions on a restricted sample of workers with a vocational education and training degree. In the Appendix, we report the results for the full sample. The most striking finding from the decomposition analyses is that changes in skill requirements largely account for changes in wages and that the effects are non-monotonic, which emphasizes the necessity for a detailed decomposition at different parts of the distribution. Specifically, we find that changes in the composition of skills only play a minor role in the VET sample. These results show that the underlying skill bundles of the restricted sample of VET workers change in parallel so that they do not provide a large source of wage heterogeneity during the observation period. However, the returns to skills are changing rather dramatically and contribute to a large part to the observed changes in wages. Changes in returns to skills are most pronounced during the 1990s and the mid-2000s. In earlier years, changes in returns to other characteristic such as e.g., experience are largely driving wage inequality.

Between 1991 and 1999, top-wage inequality increases by about five log points and bottom-end inequality increases by about three log points. Wages increase both at the top and in the middle of the distribution, and these increases are largely driven by increases in returns to cognitive skills. Specifically, at the top, increases in the returns to cognitive skills account for about 65 percent of the wage structure effect. In addition, in the middle, increases in returns to manual skills are increasing the 50-10 gap. Between 1999 and 2006, top-end wage inequality increases by another five log points and bottom-end inequality increases by about seven log points. Again, increases in the returns to skills are again largely driving these increases in inequality. At the upper part of the distribution, increases in the returns to cognitive skills account for about 95 percent of the wage structure effect. At the lower part of the distribution, increases in the returns to manual skills account for more than 100 percent of the wage structure effect.

From the beginning of the 1990s through the mid-2000s, at the top, changes in skill requirements benefit workers with large shares of cognitive skills, whereas workers with large shares of interactive or manual skills are excluded from the wage increase. In the middle of the distribution, throughout the 1990s, changes in skill requirements benefit workers with a larger share of both cognitive and manual skills, whereas workers with large shares of interactive skills are excluded from the wage increase. From 1999 to 2006, returns to cognitive skills are no longer increasing for workers in the middle. However, workers with large shares of manual skills are still largely benefitting from increasing returns to manual skills. The reason why changes affect upper- and lower-tail inequality differently is that differently skilled workers are not uniformly distributed along the wage distribution.

We conclude that workers react differently to technological change and that education curricula should be revised and updated according to changes in the demand for skills. The difference in educational systems in Germany and Anglo-Saxon countries might explain why Germany did not experience the same dramatic wage shifts. A VET system that is market-driven and where firms contribute in designing education curricula seems to be an efficient and sustainable educational system.

4.7 Appendix

Table A.4.1: Descriptive statistics of the full sample

	Log real daily wages		
	Observations	Mean	St. Dev.
Panel A. Men			
1978-79	389,409	3.731	0.263
1985-86	384,267	3.785	0.307
1991-92	424,320	3.828	0.314
1998-99	393,043	3.826	0.361
2005-06	381,962	3.790	0.431
Panel B. Women			
1978-79	187,016	3.372	0.394
1985-86	195,681	3.431	0.413
1991-92	237,496	3.519	0.424
1998-99	218,414	3.563	0.458
2005-06	191,090	3.528	0.521

Notes: SIAB data 1978-2006, authors' calculations.

Figure A.4.1: Changes in log wages by percentile, male workers, 1978 to 2006

Notes: Sample includes male employees in West Germany aged 20-60, working full-time. Wages are based on average daily earnings, in euro, and deflated to 1978 wages. Wages that are centered at social security maximum are stochastically allocated based on a Tobit model.
SIAB data 1978-2006, authors' calculations.

Figure A.4.2: Changes in log wages by percentile, female workers, 1978 to 2006

Notes: Sample includes female employees in West Germany aged 20-60, working full-time. Wages are based on average daily earnings, in euro, and deflated to 1978 wages. Wages that are centered at social security maximum are stochastically allocated based on a Tobit model.
SIAB data 1978-2006, authors' calculations.

Table A.4.2: Aggregate decomposition results, full sample

Inequality Measure	90-10	90-50	50-10
A: 1978/79 to 1985/86			
Total Change	0.0768***	0.0662***	0.0106***
	(0.00006)	(0.00033)	(0.00027)
Composition	-0.0137***	-0.0163***	0.0026***
	(0.00021)	(0.00057)	(0.00036)
Wage Structure	0.0905***	0.0826***	0.0079***
	(0.00023)	(0.00068)	(0.00045)
B: 1985/86 to 1991/92			
Total Change	-0.0007***	-0.0249***	0.0242***
	(0.00001)	(0.00035)	(0.00036)
Composition	-0.0040***	-0.0322***	0.0282***
	(0.00012)	(0.00020)	(0.00032)
Wage Structure	0.0033***	0.0072***	-0.0039***
	(0.00005)	(0.00039)	(0.00044)
C: 1991/92 to 1998/99			
Total Change	0.1166***	0.0512***	0.0654***
	(0.00035)	(0.00025)	(0.0006)
Composition	0.0623***	0.0470***	0.0153***
	(0.00067)	(0.00039)	(0.0011)
Wage Structure	0.0550***	0.0050***	0.0500***
	(0.00071)	(0.00046)	(0.0012)
D: 1998/99 to 2005/06			
Total Change	0.1959***	0.0653***	0.1306***
	(0.00095)	(0.00023)	(0.00118)
Composition	0.0464***	0.0153***	0.0312***
	(0.00072)	(0.00004)	(0.00076)
Wage Structure	0.1487***	0.0501***	0.0986***
	(0.00097)	(0.00029)	(0.00126)

Notes: SIAB data linked with BIBB/IAB Employment Surveys.
Standard errors are in parentheses.
Significance levels: * < 0.1; ** < 0.05; *** < 0.01.

Table A.4.3: Detailed decomposition results, 1978/79-1985/86, full sample

Inequality Measure	90-10	90-50	50-10
A: Detailed Composition Effects			
Cognitive Skills	0.0195***	0.0109***	0.0086***
	(0.00007)	(0.00013)	(0.00005)
Interactive Skills	0.0223***	0.0139***	0.0084***
	(0.00014)	(0.00015)	(0.00002)
Manual Skills	-0.0122***	-0.0083***	-0.0039***
	(0.00015)	(0.00039)	(0.00024)
Individual Controls	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes
Total Composition Effect	-0.0137***	-0.0163***	0.0026***
	(0.00021)	(0.00057)	(0.00036)
B: Detailed Wage Structure Effects			
Cognitive Skills	0.0335***	0.0256***	0.0079***
	(0.00004)	(0.00019)	(0.00015)
Interactive Skills	0.0030***	0.0014***	0.0017***
	(0.00004)	(0.00017)	(0.00013)
Manual Skills	0.0454***	0.0302***	0.0152***
	(0.00018)	(0.00058)	(0.00040)
Individual Controls	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes
Total Wage Structure Effect	0.0905***	0.0826***	0.0079***
	(0.00023)	(0.00068)	(0.00045)

Notes: SIAB data linked with BIBB/IAB Employment Surveys.
Standard errors are in parentheses.
Significance levels: * < 0.1; ** < 0.05; *** < 0.01.

Table A.4.4: Detailed decomposition results, 1985/86 – 1991/92, full sample

Inequality Measure	90-10	90-50	50-10
A: Detailed Composition Effects			
Cognitive Skills	-0.0048 (0.00006)	-0.0030 (0.00007)	-0.0018*** (0.00001)
Interactive Skills	-0.0384*** (0.00011)	-0.0282*** (0.00018)	-0.0102*** (0.00007)
Manual Skills	-0.0019*** (0.00002)	-0.0011*** (0.00002)	-0.0007*** (0.00004)
Individual Controls	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes
Total Composition Effect	-0.0040*** (0.00012)	-0.0322*** (0.00020)	0.0282*** (0.00032)
B: Detailed Wage Structure Effects			
Cognitive Skills	-0.0052 (0.00001)	-0.0001 (0.00030)	-0.0051*** (0.00031)
Interactive Skills	0.0282*** (0.000004)	0.0273 (0.00029)	0.0009** (0.00028)
Manual Skills	0.0032*** (0.000002)	0.0015*** (0.00020)	0.0016*** (0.00020)
Individual Controls	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes
Total Wage Structure Effect	0.0033*** (0.00005)	0.0072*** (0.00039)	-0.0039*** (0.00044)

Notes: SIAB data linked with BIBB/IAB Employment Surveys.
Standard errors are in parentheses.
Significance levels: * < 0.1; ** < 0.05; *** < 0.01.

Table A.4.5: Detailed decomposition results, 1991/92 – 1998/99, full sample

Inequality Measure	90-10	90-50	50-10
A: Detailed Composition Effects			
Cognitive Skills	-0.0141***	-0.0060***	-0.0082***
	(0.00014)	(0.00009)	(0.00023)
Interactive Skills	0.0422***	0.0389***	0.0033***
	(0.00041)	(0.00027)	(0.00068)
Manual Skills	0.0130***	0.0204***	-0.0074***
	(0.00055)	(0.00034)	(0.00089)
Individual Controls	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes
Total Composition Effect	0.0623***	0.0470***	0.0153***
	(0.00067)	(0.00039)	(0.00106)
B: Detailed Wage Structure Effects			
Cognitive Skills	0.0442***	0.0177***	0.0265***
	(0.00058)	(0.00043)	(0.00101)
Interactive Skills	-0.0164***	-0.0096***	-0.0068***
	(0.00020)	(0.00016)	(0.00037)
Manual Skills	0.0399***	0.0044***	0.0355***
	(0.00092)	(0.00063)	(0.00155)
Individual Controls	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes
Total Wage Structure Effect	0.0550***	0.0050***	0.0500***
	(0.00071)	(0.00046)	(0.00117)

Notes: SIAB data linked with BIBB/IAB Employment Surveys.
Standard errors are in parentheses.
Significance levels: * < 0.1; ** < 0.05; *** < 0.01.

Table A.4.6: Detailed decomposition results, 1998/99 – 2005/06, full sample

Inequality Measure	90-10	90-50	50-10
A: Detailed Composition Effects			
Cognitive Skills	0.0021*** (0.00037)	-0.0018*** (0.00010)	0.0039*** (0.00047)
Interactive Skills	-0.0011*** (0.00007)	-0.0005*** (0.00004)	-0.0006*** (0.00003)
Manual Skills	-0.0281*** (0.00046)	0.0119*** (0.00012)	-0.0400*** (0.00059)
Individual Controls	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes
Total Composition Effect	0.0464*** (0.00072)	0.0153*** (0.00004)	0.0312*** (0.00076)
B: Detailed Wage Structure Effects			
Cognitive Skills	0.0313*** (0.00184)	0.0066*** (0.00052)	0.0247 (0.00236)
Interactive Skills	0.0251*** (0.00255)	-0.0080*** (0.00080)	0.0331*** (0.00335)
Manual Skills	0.1302*** (0.00146)	-0.0148*** (0.00043)	0.1450*** (0.00189)
Individual Controls	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes
Total Wage Structure Effect	0.1487*** (0.00097)	0.0501*** (0.00029)	0.0986*** (0.00126)

Notes: SIAB data linked with BIBB/IAB Employment Surveys.
Standard errors are in parentheses.
Significance levels: * < 0.1; ** < 0.05; *** < 0.01.

Table A.4.7: Vocational occupations in Germany

Title of Occupation	
Miners, Stone-breaker, Mineral Processing	Beverage Production, Milk Production
Concrete and Cement Finisher,	Bricklayer, Mason
Potter, Ceramicist, Gaffer	Carpenter
Chemical Processing	Road Builder
Plastics and Polymer Processing	Plasterer
Paper and Pulp Processing	Interior Decorator, Interior Designer
Printer, Typesetter, Typographer	Joiner, Cabinet Maker
Wood, Lumber, and Timber Processing	Painter
Metal and Iron Manufacturer	Product Tester
Molding, Shaping	Crane Driver, Crane Operator, Skinner,
Metal Presser and Molder	Technical Service Personnel
Metal Polisher, Sander, Buffer	Sales Personnel
Welder, Brazing, Soldering	Banker
Blacksmith, Farrier, Forger, Plumber	Traders, Trading Personnel
Locksmith	Truck Driver, Conductor
Mechanic, Machinist, Repairmen	Sailor, Seaman, Navigator, Mariner
Tool and Dye Maker, Instrument Mechanic	Mail Carrier and Handler, Postal Clerk
Metal Craftsman	Storekeeper, Warehouse Keeper
Electrician, Electrical Installation	Accountant, Bookkeeper
Assembler	Office Clerk
Weaver, Spinner, Knitter, Wool Trade	Guard, Watchman, Police, Security Personnel
Tailor, Textile Worker	Musician
Shoemaker	Nurse, Dietician, Physical Therapist
Baker	Personal Hygiene Technician
Butcher	Cleaning Service Worker

Notes: list provided by the SIAB.
Translation taken from Gathmann and Schoenberg (2010).

CHAPTER 5

Summary and Conclusion on the Returns to Investment in Vocational Education and Training

This doctoral thesis contributes to the research on human capital investments by empirically analyzing how to secure returns on such investments for different actors in the educational system. Throughout the chapters, the focus lies on vocational education and training (VET), where both firms and individuals are involved in the investment decision. For firms, realizing a return on investment crucially depends on whether they are able to retain the workers they have trained in order to build up a highly productive workforce. For individuals, realizing a return on investment crucially depends on whether they acquire a skill set that is productive in many different firms in order to stay flexible and to maximize earnings. Moreover, to secure returns in the long run, both actors have to invest in skill sets that allow adapting to changing market environments. In a series of empirical investigations, this doctoral thesis yields important new insights into successful investment strategies for firms and individuals, both in the short and in the long run.

Returns to education from the firm's perspective: retaining VET graduates

In my first contribution, I investigate a strategy, which allows training firms embedded in weakly regulated labor markets to retain their training graduates. The new training literature explains a firm's incentive to invest in general training through the existence of imperfect labor markets. This literature argues that labor market institutions and regulations allow training firms to pay their graduates less than the market wage for skilled workers, thereby recouping their initial investment costs. However, this explanation is difficult to reconcile for countries such as Switzerland with a highly successful training system but a weakly regulated labor market. The question therefore arises of why Swiss firms would provide and pay for training if they cannot rely on a favorable market environment that secures them a return on their investment.

The solution I investigate is a firm-based strategy that is independent from external market conditions. Combining findings from the new training literature with personnel economic theory, I argue that training firms can use performance pay to incentivize their most productive graduates to stay. These graduates have two main reasons to stay: First, they expect a higher compensation because performance pay rewards their individual productivity. Second, they expect to gain from positive externalities from training. Therefore, the most productive graduates should reach their highest productivity and thus their highest wage level with the current training firm, providing them with a strong incentive to stay.

The empirical analysis confirms my hypothesis. I find that training firms that use performance pay have a significantly higher rate of internal training graduates—defined as the proportion of VET graduates staying with the training firm with respect to all VET workers in that firm—than training firms that use fixed pay. I show that imperfect labor markets might not be a necessary condition for firms to invest in general training. Instead, in weakly regulated labor markets, training firms might resort to different strategies to incentivize their graduates to stay.

This chapter thus contributes to the new training literature by providing an additional answer to the question of why firms would offer and pay for general training. I argue and provide evidence that training firms in weakly regulated labor markets might resort to different payment strategies to incentivize their graduates to stay. Therefore, I show that strong labor market regulations and institutions are not a *conditio sine qua non* for an effective Germanic-style dual VET system.

Returns to education from the individual's perspective: mobility and wages

In my second contribution, I analyze individual investment decisions and focus on the skill set that individuals acquire during their vocational education. I investigate the value of different types of skill sets and show how these skill sets determine individuals' labor market transitions.

To empirically measure the specificity of VET occupations, I apply Lazear's skill weights model (2009). Lazear assumes that single skills are general in nature but firms use them in different combinations and with different weights. His approach provides an ideal foundation to operationalize the specificity of VET occupations. I characterize these occupations by bundles of single skills and build occupation-specific skill weights to measure their degree of specificity. I then investigate whether, and if so, how the so degree of specificity determines worker mobility. I define mobility as the ease with which workers can switch between occupations.

Lazear's model also allows investigating the relationship between specificity and wages. Lazear assumes that the higher the specificity, the higher the wage but the higher also the wage loss after layoffs. I analyze if these predictions can be verified empirically. Finally, I construct a measure for the skill distance between occupations, drawing on recent literature that investigates the source of human capital specificity (Poletaev and Robinson 2008; Gathmann and Schoenberg 2010; Robinson 2011). The skill distance indicates how similar two occupations are in terms of their underlying skills.

I find that VET occupations differ greatly in their degree of specificity and that this degree of specificity largely determines workers' mobility and wages. First, I show that workers trained in more specific occupations are indeed less mobile than workers trained in more general occupations. Second, I find that the degree of specificity has a significantly positive effect on wages. Individuals trained in more specific occupations receive a wage premium compared to individuals in less specific occupations. Third, I find that the larger the skill distance between two occupations, the higher the wage loss for workers who change between these occupations. Taken together, these findings suggest a risk-return trade-off for investments in more specific skill bundles. While workers trained in more specific occupations are less mobile than workers in more general occupations, they are compensated for their lower mobility with higher wages.

Returns to education and technological change: changing demand for skills

In the second chapter, I assume that skill bundles are time constant. This assumption implies that, for example, a machinist who received his vocational education in the 1990s has the same skill set as a machinist who received it in the 2000s. Since my observation period covers six years only, this assumption should hold for the analysis. However, if I enlarge the observation period, this assumption is unlikely to hold. Of course, occupational skill bundles might adjust to changing demands for skills.

In my third contribution, I relax the assumption of time-constant skill bundles and investigate how changes within occupational skill bundles affect workers' wages. More specifically, I investigate how structural change and technological shifts affect the overall demand for skills and how this changing demand affects the market value of individuals' human capital. Taking advantage of a unique data set that provides longitudinal information on occupational skill bundles, I construct time-variant skill bundles, distinguishing between cognitive, interactive, and manual skills. I then investigate how the share of these skills changes within occupations and relate these changes to changes in the wage structure.

I document large changes in skill requirements over the observation period. The way in which these changes affect workers' wages depends on their skill bundles. As a general result, increasing returns to cognitive skills have led workers with large shares of cognitive skills to experience large wage gains, while decreasing returns to manual skills have led workers with large shares of manual skills to experience wage losses. The reason why skill changes affect inequality differently at different parts of the distribution is that differently skilled workers are not uniformly distributed along the wage distribution. In addition, I show that wages of middle-skilled workers behaved similarly to the ones of the overall population: Wages fell rather sharply at the bottom end; they increased rather sharply at the top end, and increased more modestly in the middle.

My full sample analysis reveals that, overall; wages of middle-skilled workers have remained largely stable. I do not find strong evidence that middle-skilled workers have been hit particularly hard by technological change, as it has been the case for the US and the UK. In Germany, technological change has not made middle-skill occupations obsolete, but rather the skill requirements within occupations have fundamentally changed. Because the wages of middle-skilled have remained largely stable over the observation period, my analysis suggests that middle-skilled workers were able to adapt to these technological changes.

Implications for the firm and the individual

Combining the findings of my three contributions reveals several important insights into what firms and individuals can do to secure returns on their educational investments. From the firm's point of view, the analyses show that firms' training participation does not exclusively depend on a favorable market environment. Instead, firms might as well use their internal resources to incentivize their graduates to stay. An example of such an internal resource is the use of performance pay. If firms can minimize the risk of losing newly trained workers, they will also be more willing to provide general training instead of firm-specific training. General training should in turn incentivize individuals to participate in training, because they acquire skills that improve their mobility and earnings.

In addition, my analyses suggest that firms' involvement in the design of education curricula is crucial for ensuring that graduates obtain labor market relevant skills that prepare them to cope with technological change. Indeed, while most Anglo-Saxon countries underwent dramatic changes in wages and labor force participation of their middle-skilled workers, wages and employment of middle-skilled workers remained largely stable in countries such as Germany, where training firms take a leading part in designing VET curricula.

From the individual's point of view, the analyses show that skill specificity hinders workers' mobility in both the short term and the long term. While workers are compensated with a wage premium for the lower mobility in the short run, skill specificity is likely to turn into a disadvantage in the long run whenever market forces fundamentally change the demand for skills. If individuals specialize in a small number of skills only and those skills become obsolete, their human capital becomes obsolete as well. Individuals should therefore acquire a broader skill set to diversify their risk. Moreover, they are well advised to participate in further training to update their skills in accordance with changing skill demands.

Aligning the interests of firms and individuals

My analyses provide a more differentiated picture of both the conflicting and the compatible interests of firms and individuals. Their interests are conflicting when focusing on the short run. While individuals prefer training in more general skills to ensure their labor market flexibility, firms are more inclined to invest in more specific training, precisely because of graduates' limited outside options, which minimizes firms' risk of losing them. To align these conflicting interests and to incentivize both actors to participate in training, curricula should be neither completely specific nor completely general. While they should be specific to the extent that firms profit more from participating in training than from hiring externally trained workers, they should also be sufficiently general to ensure graduates' mobility.

However, firms' and individuals' interests are largely compatible when focusing on the long run. To secure returns to education in the long run, individuals need to have a broad knowledge and skill base, which allows them to respond to changing skill demands and to acquire new skills over their career cycle. Because foreseeing future market dynamics is almost impossible, only this broad base endows individuals with the possibility of adapting to change. The most rationale strategy appears to be hedging the risk and investing in a more general skill set in which the depreciation of one skill can be counteracted by the appreciation of another skill.

This strategy makes sense both for firms and individuals. Although workers' flexibility increases a firm's risk of losing them to competitors, it also increases firm performance in the long run. If firms had a highly specifically trained workforce, they would need to replace it with each new technology wave. Contrarily, a more generally trained workforce that is keeping up with the technological frontier through continuous training, allows firms to react quickly to technological change and to exploit it for their benefit.

Therefore, both firms and individuals are likely to achieve higher benefits from general training than from specific training. The crucial point of discussion thus is how to align these long-term interests with short-term incentives. One promising solution might be to use performance pay. My analyses show that graduates are more inclined to stay with their training firm if their wages have a performance pay component, which guarantees them a direct reward for their higher productivity. Similarly, incumbent workers will be more inclined to stay and work harder if firms use performance pay.

Ideas for future research

In a next step, it would be fruitful to replicate my studies with data from different countries. For the first project, it would be particularly interesting to use data from countries with a strong VET system and a similar labor market regime as Switzerland, such as Denmark, to investigate if one can find a similar performance pay effect. In addition, an analysis of what types of firms participate in training might produce highly insightful results. Because performance pay firms have a higher retention success than firms with fixed salaries, one should find that these performance pay firms should also be more likely to invest in training.

Regarding the second project, one could further investigate whether the VET content is more or less specific in Switzerland than it is in other countries and whether, consequently, VET workers differ in their mobility across countries.

Finally, drawing on findings from the third project, one could focus on workers in occupations that disappear due to technological change. Following the labor market transitions of workers in these occupations would allow a better understanding of how workers in such disappearing occupations cope with the fact that most of their skills have become obsolete.

Policy implications and conclusion

My findings point to several policy implications. First, as it is already in practice in Switzerland, policy makers should actively involve firms in updating education curricula and defining further training contents. Whenever firms experience changes in the market environment, they should be able to transfer these changes to the educational system to ensure that apprentices acquire knowledge that is at the technological frontier.

Second, policy makers should be made more aware that continuous training and lifelong learning are crucial for incumbent workers to keep up with technological change. While many studies for the United States and the United Kingdom paint a dark picture for middle-skilled workers, my analyses for Germany reveal that middle-skilled workers have hardly lost any ground. I show that technological change has not made all middle-skill occupations obsolete. Rather, technological change has depressed the demand for certain types of skills, while it has increased the demand for other types.

Skill bundles within occupations have adapted to technological change and those workers who have adjusted their skill bundles accordingly were able to benefit from these changes. If workers remained with their original skill bundles, they would have had to face large depreciation rates on their human capital. However, workers who acquired the newly required skills, could actively participate in and benefit from technological change. A workforce whose skills are up-to-date improves the productivity of firms, enhances the labor market opportunities of workers, and accelerates overall economic growth.

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